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Vehicle stock modelling in long term projections

Survey of the literature

July 2017

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Responsible publisher: Philippe Donnay
Legal Deposit: D/2017/7433/21

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Abstract - Transport models used for long-term projections should reflect the impact of shared, automated and electric mobility modes. The objective of the current paper is to derive lessons from the existing literature on vehicle ownership modelling to find options to further improve the PLANET model, which is used for projections of transport demand in Belgium.

PLANET is already well equipped to represent the impacts of shared and automated cars on the opportunity cost of travel time, the load factors and the annual mileage of cars.

Our key conclusion is that the modelling approach taken should depend on the time perspective of the model and on the availability of data. In the short run (up to 5 years in the future), consumer preferences and vehicle technologies can be assumed to remain stable, and the evaluation of policies is best based on econometric models. In the long run (more than 15 years in the future), preferences and technologies are fundamentally uncertain, and a scenario approach is more appropriate than forecasting. For medium term projections (5 to 15 years in the future), we propose to enrich existing econometric models with models of social learning by households and of learning-by-doing by firms. The "synthetic utility" approach holds the most promise for rapid integration in PLANET of vehicle types that currently have low or zero market shares, but are expected to have an important potential in the long run, such as electric and automated vehicles.

Abstract - Les modèles de transport utilisés pour les perspectives à long terme devraient refléter l'impact des modes de transport partagés, automatisés et électriques. La présente analyse vise à explorer la littérature existante sur la modélisation du parc automobile pour identifier les options susceptibles d'améliorer le modèle PLANET utilisé pour établir les perspectives de la demande de transport en Belgique.

PLANET est déjà un modèle approprié pour représenter l'impact des voitures partagées et automatisées sur le coût d'opportunité du temps de déplacement, le taux d'occupation et le kilométrage annuel des voitures.

Notre principale conclusion est que l'approche à retenir pour la modélisation devrait dépendre de l'horizon du modèle et de la disponibilité de données. À court terme (sur un horizon de 5 ans maximum), on peut considérer que les préférences des consommateurs et les technologies automobiles resteront stables, et il est préférable que l'évaluation des politiques se fonde sur des modèles économétriques. À long terme (sur un horizon de plus de 15 ans), les préférences et les technologies sont fondamentalement incertaines, et il convient de suivre une approche par scénarios plutôt que d'émettre des prévisions. Pour les perspectives à moyen terme (sur un horizon de 5 à 15 ans), nous proposons d'enrichir les modèles économétriques existants de modèles d'apprentissage social par les ménages et d'apprentissage par la pratique par les sociétés. L'approche de l'« utilité synthétique » est la plus prometteuse pour une intégration rapide dans PLANET des types de véhicules qui ont actuellement une part de marché nulle ou très limitée, mais qui représentent un potentiel important à long terme, comme les véhicules électriques et automatisés.

Abstract - Transportmodellen die worden gebruikt voor langetermijnvooruitzichten zouden de impact van gedeelde, geautomatiseerde en elektrische vervoerswijzen moeten weerspiegelen. Deze paper heeft tot doel lessen te trekken uit de bestaande literatuur rond het modelleren van het wagenpark om het PLANET-model – dat wordt gebruikt om vooruitzichten van de transportvraag in België op te stellen – verder te verbeteren.

Het PLANET-model kan nu al gemakkelijk gebruikt worden om de impact voor te stellen van gedeelde en geautomatiseerde wagens op de opportuniteitskosten van de reistijd, de bezettingsgraad en het aantal jaarlijks afgelegde kilometers van wagens.

De belangrijkste conclusie is dat de modelbenadering afhankelijk zou moeten zijn van het tijdperspectief van het model en de beschikbaarheid van de gegevens. Op korte termijn (tot vijf jaar in de toekomst) worden de consumentenvoorkeuren en de voertuigtechnologieën verondersteld stabiel te blijven en worden de beleidsmaatregelen het best geëvalueerd aan de hand van econometrische modellen. Op lange termijn (meer dan vijftien jaar in de toekomst) zijn voorkeuren en technologieën fundamenteel onzeker en is een benadering op basis van scenario's meer geschikt dan vooruitzichten. Voor de langetermijnvooruitzichten (vijf tot vijftien jaar in de toekomst) stellen we voor om de bestaande econometrische modellen uit te breiden met modellen die het leren door nabootsing van de huishoudens en het 'al doende leren' door ondernemingen integreren. Het gebruik van synthetische nutsfuncties is zeer waarschijnlijk het meest geschikt om vlug voertuigtypes in het PLANET-model te integreren die op dit moment weinig of geen marktaandelen hebben, maar waarvan wordt verwacht dat ze veel potentieel zullen hebben op lange termijn, zoals elektrische en geautomatiseerde voertuigen.

Jel Classification - H23, C25, L62, L9, O3, Q47, Q5, R4
Keywords - transport demand, long-term forecasting, technology diffusion, car ownership, automated vehicles, shared mobility, electric vehicles, integrated energy-transport modelling

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Executive summary

It is expected that some externalities caused by the transport sector will get worse in the future, especially greenhouse gas emissions, congestion and local air pollution. However, the transport sector is also on the brink of a possibly transformative change caused by the simultaneous rise of shared, automated and electric mobility modes. The actual growth potential of these new technologies and business models and their impact are highly uncertain.

Depending on the policy context, they could solve the major externalities caused by transport, or exacerbate them to the point of disaster. On the one hand, the number of cars needed to satisfy mobility demand is likely to drop significantly if shared and automated cars become commonplace. On the other hand, the need to reposition shared and automated cars to get new passengers is likely to lead to a dramatic increase in vehicle kilometres, and to a much higher turnover of the vehicle stock.

Transport models thus need to be adapted to reflect the impact of these developments. The current paper focuses on the issue of vehicle ownership modelling in long-term projections. Our objective is to derive lessons from the existing literature to find options to further improve the PLANET model, which has been developed by the Federal Planning Bureau to provide long-term projections of transport demand in Belgium.

Vehicle stock models are usually embedded in broader models, which also include projections of total mobility demand, modal choices, route choices etc. The representation of the vehicle stock is therefore related to other key choices in the design of the transport model, especially:

– The integration of the transport model in a model of the wider economy;
– The relation between overall travel demand and vehicle choice;
– The treatment of indirect emissions;
– The opportunity cost of time spent travelling;
– The relative weight given to explicit economic modelling versus expert judgement.

The PLANET model can be described as a *sectoral* model of the transport sector, which follows the "service demand approach": it first models travel demand for all modes combined, and then allocates total demand to individual modes. The total number of cars is determined at the aggregate level as the number of cars that is needed to meet the expected mobility demand. Aggregate demand is further split over individual vehicle classes. No attempt is made to estimate the number of cars at the household level. PLANET considers only well-to-wheel emissions. For instance, it does not consider the environmental effects of the production and the scrapping of vehicles. The opportunity cost of time is included in the generalised cost of transport. Therefore, PLANET is well equipped to represent that automated cars reduce the opportunity cost of travel time.

In its representation of transport technologies, PLANET is a "hybrid" model: for passenger cars, the demand is explicitly modelled in detail while the technologies for other modes are described at a higher level of abstraction. It is thus neither a pure "top-down" nor "bottom-up" model.

Several models represent non-technical parameters, such as the heterogeneity of the households, social influences and contextual conditions. PLANET, in contrast, does not account for individual household characteristics. Linking vehicle registration data with household surveys holds some potential to improve the representation of consumer behaviour in PLANET.

One increasingly important issue is the demand for vehicle types that have currently low or zero market shares, but that are expected to have an important potential in the long run, such as electric and automated vehicles. The most promising approach to deal with this issue consists in combining observations of 'real' markets with outcomes of 'hypothetical' markets. Alternatively, one can use "synthetic utility functions", whose parameters are based on "first principles" or extensive literature surveys rather than on individual studies that use limited samples in a specific context. Taking into account data availability in Belgium, the "synthetic utility" approach holds the most promise for rapid integration in the existing version of PLANET.

Of all the approaches to vehicle stock modelling in long term projections, the one with the most solid foundations in economic theory consists in taking the annual sales of vehicles as "residual" variable:

- The existing stock of vehicles is retired according to a scrappage function.
- The total vehicle stock is estimated as the stock that is *needed* to meet travel demand (expressed in passenger kilometres), taking into account load factors and the average vehicle kilometres for existing vehicles.
- The annual vehicles sales are calculated as the desired car stock minus the actual car stock inherited from previous vintages.
- Total sales are split in classes (e.g. according to fuel or vehicle size) using a discrete choice function.

In order to represent the impact of shared mobility, it is important that parameters such as the load factors and the annual mileage of cars can be modified according to the scenario that is under consideration. The PLANET model can be readily modified to deal with this requirement.

Our key conclusion is that the modelling approach taken should depend on the time perspective of the model and on the availability of data. In the short run (up to 5 years in the future), consumer preferences and vehicle technologies can be assumed to remain stable, and the evaluation of policies is best based on econometric models. In the long run (more than 15 years in the future), preferences and technologies are fundamentally uncertain, and a scenario approach is appropriate: models should explore possible futures, and outline the implications of the most extreme scenarios that still seem plausible. For medium term projections (5 to 15 years in the future), we propose to start with existing econometric models, but enriched with models of social learning by households and of learning-by-doing by firms. Repeated simulations with random changes in the values of the key parameters will help us understand the robustness of our projections.

Synthèse

On s'attend à une dégradation de certaines externalités causées par le secteur des transports dans le futur, particulièrement les émissions de gaz à effet de serre, la congestion et la pollution atmosphérique au niveau local. Toutefois, le secteur des transports se trouve également à l'aube d'une mutation peut-être radicale en raison de la percée simultanée des modes de transport partagés, automatisés et électriques. Le potentiel de croissance réel de ces nouvelles technologies et modèles économiques et leur impact se caractérisent par une grande incertitude.

Selon l'orientation politique choisie, ils pourraient résoudre les externalités majeures causées par le transport ou, à l'inverse, les exacerber tant et plus. D'un côté, le nombre de voitures nécessaire pour satisfaire la demande de mobilité est susceptible d'enregistrer une baisse sensible si les voitures partagées et automatisées viennent à être utilisées couramment. D'un autre côté, la nécessité de repositionner les voitures partagées et automatisées pour que de nouveaux passagers puissent les utiliser est susceptible d'entraîner une croissance spectaculaire du nombre de véhicules-kilomètres ainsi qu'une rotation bien plus rapide du parc automobile.

Les modèles de transport doivent donc être adaptés pour refléter l'impact de ces développements. La présente analyse se penche sur la problématique de la modélisation du parc automobile dans les perspectives à long terme. L'objectif poursuivi est d'explorer la littérature existante pour identifier les options susceptibles d'améliorer le modèle PLANET élaboré par le Bureau fédéral du Plan dans le but de réaliser des perspectives de la demande de transport en Belgique.

Les modèles de parc automobile sont habituellement intégrés dans des modèles plus larges, qui englobent également des perspectives de la demande totale de transport, des choix de modes de transport, des choix de route, etc. Par conséquent, la représentation du parc automobile est liée à d'autres choix fondamentaux dans la conception du modèle de transport, spécialement :

– L'intégration du modèle de transport dans un modèle de l'économie au sens large ;
– La relation entre la demande totale de transport et le choix du véhicule ;
– Le traitement des émissions indirectes ;
– Le coût d'opportunité du temps de déplacement ;
– Le poids relatif donné à la modélisation économique explicite par rapport à l'avis d'experts.

Le modèle PLANET peut être décrit comme un modèle sectoriel dans le domaine du transport qui suit l'approche de la demande de services : tout d'abord, il modélise la demande de transport pour l'ensemble des modes de transport, puis il répartit la demande totale entre les différents modes de transport. Le nombre total de voitures est déterminé au niveau agrégé. Il correspond au nombre de voitures nécessaire pour satisfaire la demande attendue de transport. La demande agrégée est ensuite ventilée entre les différentes catégories de véhicules. Cette approche ne cherche pas à estimer le nombre de voitures au niveau des ménages. PLANET ne tient compte que des émissions « du puits à la roue ». Par exemple, il ne tient pas compte de l'impact environnemental de la production et de la mise à la casse des véhicules.

Le coût d'opportunité du temps de déplacement est inclus dans le coût généralisé du transport. Par conséquent, PLANET est un modèle approprié pour rendre compte du fait que les voitures automatisées réduisent le coût d'opportunité du temps de déplacement.

Dans sa représentation des technologies de transport, PLANET est un modèle « hybride » : pour les voitures particulières, la demande est explicitement modélisée de manière détaillée, tandis que les technologies utilisées pour d'autres modes sont décrites à un niveau d'abstraction plus élevé. Ce n'est donc pas un modèle purement « top-down » ou « bottom-up ».

Plusieurs modèles tiennent compte de paramètres non techniques, comme l'hétérogénéité des ménages, des influences sociales et des facteurs contextuels. En revanche, PLANET ne tient pas compte des caractéristiques individuelles des ménages. Relier les données sur les immatriculations de véhicules aux enquêtes réalisées auprès des ménages offre certaines possibilités d'améliorer la représentation du comportement des consommateurs dans PLANET.

La demande de types de véhicules qui ont actuellement une part de marché nulle ou très limitée, mais qui représentent un potentiel important à long terme, comme les véhicules électriques et automatisés, est un aspect important qui mérite une attention accrue. À cet égard, l'approche susceptible de donner les meilleurs résultats consiste à combiner les observations de marchés 'réels' aux résultats de marchés 'hypothétiques'. Une autre méthode consiste à recourir aux fonctions d'utilité synthétique dont les paramètres se basent sur des principes d'application générale ou sur des recherches approfondies dans la littérature plutôt que sur des études individuelles qui utilisent des échantillons limités dans un contexte spécifique. Compte tenu de la disponibilité de données en Belgique, l'approche de l'utilité synthétique est la plus prometteuse pour une intégration rapide dans la version existante de PLANET.

De toutes les approches permettant de modéliser le parc automobile dans les perspectives à long terme, celle qui a l'assise la plus solide dans la théorie économique consiste à prendre les ventes annuelles de véhicules comme variable « résiduelle » :

– Dans le modèle, le parc automobile existant est progressivement retiré de la circulation selon les tendances historiques ;
– Le parc automobile total est calculé comme étant le parc *nécessaire* pour satisfaire la demande de transport (exprimé en passagers-kilomètres), en tenant compte du taux d'occupation et des véhicules-kilomètres moyens pour les véhicules existants ;
– Les ventes annuelles de véhicules sont calculées comme étant le parc automobile souhaité moins le parc automobile réel hérité des années de mise en circulation précédentes ;
– Le total des ventes est réparti en plusieurs catégories (par ex. en fonction du type de carburant ou de la taille du véhicule) en utilisant une fonction de choix discret.

Pour représenter l'impact de la mobilité partagée, il importe que des paramètres tels que le taux d'occupation et le kilométrage annuel des voitures puissent être modifiés en fonction du scénario étudié. Le modèle PLANET peut être facilement adapté pour tenir compte de cette exigence.

Notre principale conclusion est que l'approche à retenir pour la modélisation devrait dépendre de l'horizon du modèle et de la disponibilité de données. À court terme (sur un horizon de 5 ans maximum), on peut considérer que les préférences des consommateurs et les technologies automobiles resteront stables, et il est préférable que l'évaluation des politiques se fonde sur des modèles économétriques. À long terme (sur un horizon de plus de 15 ans), les préférences et les technologies sont fondamentalement incertaines, et il convient de suivre une approche par scénarios : les modèles devraient explorer les évolutions possibles et exposer les implications des scénarios plausibles les plus extrêmes. Pour les perspectives à moyen terme (sur un horizon de 5 à 15 ans), nous proposons de nous baser sur des modèles économétriques existants, mais en les enrichissant de modèles d'apprentissage social par les ménages et d'apprentissage par la pratique par les sociétés. Des simulations répétées avec des changements aléatoires de valeur pour les paramètres clés nous aideront à mieux comprendre la robustesse de nos perspectives.

Synthese

Er wordt verwacht dat bepaalde externaliteiten die door de transportsector worden veroorzaakt – in het bijzonder broeikasgasemissies, congestie en lokale luchtverontreiniging – in de toekomst nog groter zullen worden. De transportsector staat echter ook aan de vooravond van een mogelijk transformatieve verandering die wordt veroorzaakt door de gelijktijdige opkomst van gedeelde, geautomatiseerde en elektrische vervoerswijzen. Het effectieve groeipotentieel van die nieuwe technologieën en bedrijfsmodellen en de impact ervan zijn hoogst onzeker.

Afhankelijk van de beleidscontext zouden ze de voornaamste door transport veroorzaakte externaliteiten kunnen oplossen of ze daarentegen extreem verergeren. Enerzijds is het waarschijnlijk dat het aantal wagens dat nodig is om aan de mobiliteitsvraag te voldoen fors zal dalen als gedeelde en geautomatiseerde wagens gemeengoed worden. Anderzijds moeten gedeelde en geautomatiseerde wagens ook worden verplaatst om nieuwe passagiers de mogelijkheid te geven die te kunnen gebruiken, wat waarschijnlijk leidt tot een spectaculaire stijging van de voertuigkilometer en een grotere omloop van het wagenpark.

Transportmodellen moeten daarom worden aangepast om de impact van die ontwikkelingen te weerspiegelen. In deze paper wordt de kwestie van het modelleren van het wagenpark in langetermijnvooruitzichten onder de loep genomen. Deze paper heeft tot doel lessen te trekken uit de bestaande literatuur om het PLANET-model – dat door het Federaal Planbureau werd ontwikkeld om langetermijnvooruitzichten van de transportvraag in België op te stellen – verder te verbeteren.

Modellen met betrekking tot het wagenpark worden doorgaans ingebed in bredere modellen, die ook vooruitzichten van de totale mobiliteitsvraag, modale keuzes, routekeuzes, enz. bevatten. Hoe het wagenpark wordt voorgesteld is daarom afhankelijk van andere belangrijke keuzes over het ontwerp van het transportmodel, met name:

– De integratie van het transportmodel in een model van de bredere economie;
– Het verband tussen de globale mobiliteitsvraag en de voertuigkeuze;
– De verwerking van indirecte emissies;
– De opportuniteitskosten van de reistijd;
– Het relatieve gewicht dat wordt toebedeeld aan expliciete economische modellering tegenover expertmeningen.

Het PLANET-model kan worden omschreven als een *sectoraal* model van de transportsector, waarin wordt uitgegaan van de ‘vraag naar diensten’: eerst wordt de mobiliteitsvraag voor alle vervoersmodi samen gemodelleerd, waarna de totale vraag wordt toegewezen aan de individuele vervoersmodi. Het totale aantal wagens wordt op geaggregeerd niveau bepaald als het aantal wagens dat nodig is om te voldoen aan de verwachte mobiliteitsvraag. De geaggregeerde vraag wordt verder opgesplitst in individuele voertuigklassen. Er wordt geen poging gedaan het aantal wagens op het niveau van de individuele huishoudens te ramen. In PLANET wordt alleen met bron-tot-wielemissies rekening gehouden.

Er wordt bijvoorbeeld geen rekening gehouden met de milieu-effecten van de productie en de uitgebruikname van voertuigen. De opportuniteitskosten van de tijd worden opgenomen in de gegeneraliseerde transportkosten. PLANET is bijgevolg geschikt om weer te geven dat geautomatiseerde wagens de opportuniteitskosten van de reistijd kunnen verminderen.

Wat betreft de manier waarop vervoerstechnologieën worden voorgesteld, is PLANET een 'hybride' model: voor personenwagens wordt de vraag expliciet in detail gemodelleerd, terwijl de technologieën voor de overige vervoersmodi op een hoger abstractieniveau worden beschreven. Het is dus noch een puur top-down-, noch een puur bottom-upmodel.

Verschillende modellen houden rekening met het effect van niet-technische parameters, zoals de heterogeniteit van de huishoudens, sociale invloeden en randvoorwaarden. PLANET houdt daarentegen geen rekening met de individuele kenmerken van de huishoudens. Door gegevens uit de kentekenregisters te koppelen aan huishoudensenquêtes zou het consumentengedrag in PLANET beter kunnen worden weergegeven.

Een probleem dat steeds aan belang wint, is de vraag naar voertuigtypes die momenteel weinig of geen marktaandelen hebben, maar waarvan wordt verwacht dat ze veel potentieel zullen hebben op lange termijn, zoals elektrische en geautomatiseerde voertuigen. De meest veelbelovende aanpak voor dit probleem bestaat erin waarnemingen van 'reële' markten te combineren met realisaties van 'hypothetische' markten. Als een alternatief kunnen 'synthetische nutsfuncties' worden gebruikt waarvan de parameters zijn gebaseerd op 'eerste beginselen' of een uitgebreide literatuurstudie eerder dan op individuele studies die een beperkte steekproef gebruiken in een specifieke context. Als er rekening wordt gehouden met de beschikbaarheid van gegevens in België, maakt de benadering inzake 'synthetische nutsfuncties' het meeste kans om vlug te worden geïntegreerd in de bestaande PLANET-versie.

Van alle benaderingen om het wagenpark te modelleren in langetermijnvooruitzichten, bestaat de benadering met de meest solide basis in de economische theorie erin de jaarlijkse verkoop van voertuigen als een 'residuele' variabele te beschouwen:

– Het aantal voertuigen van het bestaande wagenpark dat uit gebruik wordt genomen, wordt berekend aan de hand van historische gegevens.

– Het totale wagenpark wordt geraamd als het park dat *nodig* is om te voldoen aan de mobiliteitsvraag (uitgedrukt in reizigerskilometers), waarbij rekening wordt houden met de bezettingsgraad en de gemiddelde voertuigkilometers voor bestaande voertuigen.

– De jaarlijkse verkoop van voertuigen wordt berekend als het gewenste wagenpark min het overblijvende wagenpark van de vorige jaargangen.

– De totale verkoop wordt opgesplitst in klassen (bv. volgens brandstoftype of voertuiggrootte) aan de hand van een discrete keuzefunctie.

Om de impact van gedeelde mobiliteit voor te stellen, is het belangrijk dat parameters, zoals de bezettingsgraad en het aantal jaarlijks afgelegde kilometers van wagens, kunnen worden aangepast naargelang van het scenario dat wordt gebruikt. Het PLANET-model kan gemakkelijk aan die vereiste worden aangepast.

De belangrijkste conclusie is dat de modelbenadering afhankelijk zou moeten zijn van het tijdperspectief van het model en de beschikbaarheid van de gegevens. Op korte termijn (tot vijf jaar in de toekomst) worden de consumentenvoorkeuren en de voertuigtechnologieën verondersteld stabiel te blijven en worden de beleidsmaatregelen het best geëvalueerd aan de hand van econometrische modellen. Op lange termijn (meer dan vijftien jaar in de toekomst) zijn voorkeuren en technologieën fundamenteel onzeker en is een benadering op basis van scenario's geschikt: modellen zouden mogelijke toekomsten moeten verkennen en de gevolgen schetsen van de meest extreme scenario's die nog plausibel lijken. Voor de middellangetermijnvooruitzichten (vijf tot vijftien jaar in de toekomst) stellen we voor om uit te gaan van bestaande econometrische modellen die vervolgens worden uitgebreid met modellen voor sociaal leren door huishoudens en 'al doende leren' door ondernemingen. Aan de hand van herhaalde simulaties met willekeurige veranderingen in de waarden van de belangrijkste parameters kan de robuustheid van de vooruitzichten worden nagegaan.

List of abbreviations

Abbreviation	Explanation
AFVs	Alternative fuel vehicles
ASC	Alternative Specific Constant
AV	Automated vehicle(s)
BEV	Battery Electric Vehicle
CES	Constant Elasticity of Substitution
CNG	Compressed Natural Gas
COPERT	COmputer Programme to calculate Emissions from Road Transport
EV	Electric Vehicle
FCEV	Hydrogen powered Fuel Cell Electric Vehicle
GHG	Greenhouse gas
HEV	Hybrid Electric Vehicle
HOV lanes	High-occupancy vehicle lanes
HOT lanes	High-occupancy toll lanes
IAM	Integrated Assessment Model
ICE	Internal combustion engine
ILUC	Indirect land use effects
LPG	Liquefied petroleum gas
MNL	Multinomial Logit
NMNL	Nested Multinomial Logit
PHEV	Plug-in hybrid electric
pkm	Passenger kilometre
RP	Revealed preferences
SP	Stated preferences
TCO	Total Cost of Ownership
tkm	Ton-kilometre
TMB	travel money budget
TTB	Travel time budget
vkm	Vehicle-kilometre
VOT	value of time
VTT	value of travel time
SO_X	Sulfur oxide
NO_X	Nitrogen oxide
PM	Particulate matter
WTP	willingness-to-pay

1. Introduction

Long-term projections of transport demand are essential inputs into several policy processes such as the identification of future infrastructure needs and energy requirements of the transport sector on the one hand and the expected tax revenues from the sector on the other hand. They are also needed for projections of the negative externalities of transport such as congestion and environmental damages. In Belgium, national long-term projections are provided by the PLANET model (Desmet et al. 2008, Gusbin et al. 2010), which has been developed by the Belgian Federal Planning Bureau.

Most experts agree that, without major changes in policies, technology and behaviour, some externalities caused by the transport sector will only get worse in the future. From a global perspective, the GHG emissions of the sector are a major concern, while increasing congestion affects the viability and competitiveness of cities.

However, the transport sector is also on the brink of a possibly transformative change: the simultaneous rise of the shared, automated and electric mobility. It has been argued that, depending on the policy context, this could solve the major externalities caused by transport, or exacerbate them to the point of disaster.

Transport models will need to be adapted to represent how these changes affect key parameters such as the composition of the vehicle stock, the life cycle of vehicles, the annual distances driven, the load factors of the vehicles, the environmental impacts of transport etc. The current paper will focus on the issue of vehicle stock modelling. Before proceeding, we shall however elaborate on the points raised above.

1.1. Transport at a crossroads

Transport is going through turbulent times.

On the one hand, the negative externalities of transport remain a key policy issue.

For instance, despite some successes in the reduction of the local environment impacts of the transport sector, its climatic impact continues to rise. In its most recent Transport Outlook, the OECD/ITF admits that global “CO_2 emissions from transport could increase by 60% by 2050, despite the significant technology progress already assumed in the Outlook’s baseline scenario” (OECD/ITF 2017). The OECD/ITF also expects that motorised mobility in cities is set to double between 2015 and 2050, and that the share of private cars will continue to increase strongly in developing regions, while falling only slightly in developed economies.

In the EU, it is expected (EEA 2016, p 34) that, under current policies, GHG emissions in the transport sector in 2050 will be 15% higher than in 1990, which falls significantly short of the EU’s reduction target of 60%. Moreover, although emissions of SO_X, NO_X and PM from transport activities in the EU have decreased between 2000 to 2014, passenger cars emissions of NO_X have increased by 3.3 %, as a result of increases in transport activity and the dieselisation of the car park. (EEA 2016, p 32).

In Belgium, the Federal Planning Bureau (BFP and SPF M&T, 2015) is projecting that increased congestion will cause the average speed of road transport during peak hours to decrease with 24% in 2030 compared to 2012. It is expected that, as a result of more stringent emission standards and the continued electrification of the transport sector, the direct emissions of transport will remain roughly constant or decrease. However, due to changes in the energy mix and the increasing share of biofuels, indirect emissions will increase further between 2012 and 2030: between 4 and 6% for local pollutants, and up to 16% for GHG.

On the other hand, transport is also going through a period of possibly transformative change, mainly as a result of three game changers: the rise of the collaborative or shared economy, the breakthrough of technologies for automated mobility, and major improvements in electric mobility (Franckx 2016, Fulton et al. 2017a, Arbib & Seba 2017).

Shared mobility services in the broad sense of the word[1] have indeed shown consistently solid growth over the last few years. To give a few examples, in Europe, membership of carsharing systems has grown from around 250,000 individuals in 2006 to more than 2,000,000 members in 2014 (Shaheen and Cohen 2016). In San Francisco, ridesourcing companies (such as Uber and Lyft) have now a market share of 15% of all intra-San Francisco vehicle trips (San Francisco County Transportation Authority, 2017).

We have now reached the point that some urban transport planners are already adapting their models to reflect this new reality. Major car manufacturers are now active in what was considered a fringe market just a few years ago. However, it still is a major question whether these new business models will mainly replace motorized private travel or other transport modes, and whether they have market potential outside large cities and some specific target groups. Moreover, while their growth has been spectacular, it was from an extremely low starting point, and in most places, their share in total traffic remains modest. For instance, actual membership of carsharing systems in Europe still amounts to just around 0.5% of the population of driving age (Franckx, 2016).

Automated road mobility is also going through a rollercoaster. Although several major players have developed prototypes of automated cars that can function in (controlled) operational circumstances, there is a lot of controversy regarding the future speed of adoption. One (admittedly extremely bullish) scenario (Arbib & Seba 2017) expects that, within 10 years of the widespread regulatory approval of automated vehicles (AV), 95% of the passenger km (pkm) travelled will take place in shared and electric automated vehicles. Others (such as Litman 2017) expect that costs for automated vehicle will not decrease rapidly, and do not expect a widespread adoption of autonomous vehicles before the 2040s or even 2060s.

Moreover, the evidence on whether the impacts of automated cars will be beneficial or detrimental is far from univocal. While most observers agree that, with AV, accident-rates could fall by 80 to 90 %, the impacts on congestion and pollution are ambiguous. This ambiguity can be explained as follows. On the one hand, the *direct* effect of AV is that they will lead to a more efficient-road use and decreased

[1] Shared mobility ranges from vehicle sharing in peer-to-peer systems to ridesharing services provided by ridesourcing companies (such as Uber and Lyft) or app based minibus systems. See Franckx (2016) for a more extensive typology.

congestion, thanks to a combination of shorter headways and a decrease in accidents. Platooning, a more efficient traffic flow and reduction in vehicle weight (as a result of a reduced need for safety equipment and occupant protection mass) could lead to energy savings of up-to ~80%. On the other hand, AV will lead to an increase in traffic, as they will provide personal mobility to people currently unable to drive such as young people without driving license, the physically impaired, and elderly people. Moreover, as people will be able to use the time spent in their cars for their own purposes (leisure or work), the opportunity cost of time spent in cars will decrease, which will lead to longer trips (and especially commutes). AV will also spend a significant time travelling empty to a suitable parking place (or, in the case of shared vehicles, to the next customer). More detailed discussions of these issues can be found in Franckx (2016) and Fulton et al. (2017a).

Finally, major breakthroughs in battery technology have improved the competitive position of electric vehicles (EV), even though the most performant models still target mainly an affluent niche audience. Most EV still face two major disadvantages compared to vehicles with internal combustion engine (ICE): their limited range and/or their large acquisition cost. However, both parameters are improving and much more quickly than anticipated until just a few years ago (Fulton et al. 2017a).

Arguably, the most promising aspect of these three important developments in the mobility sector (shared mobility, autonomous vehicles, electric mobility) is that they can be mutually reinforcing. On the one hand, fleet of shared vehicles can spread the high fixed cost of electrification and automation over a larger user base. Moreover, with shared vehicles, it is much easier to schedule the charging of electric vehicles and to allocate vehicles whose range correspond to the purpose of individual trips. On the other hand, self-driving vehicles solve the problem of obtaining access to shared modes, as they will drive themselves to the place where they can pick up their clients and free their users from the burden of finding a parking spot (Franckx 2016, Fulton et al. 2017a, Arbib & Seba 2017).

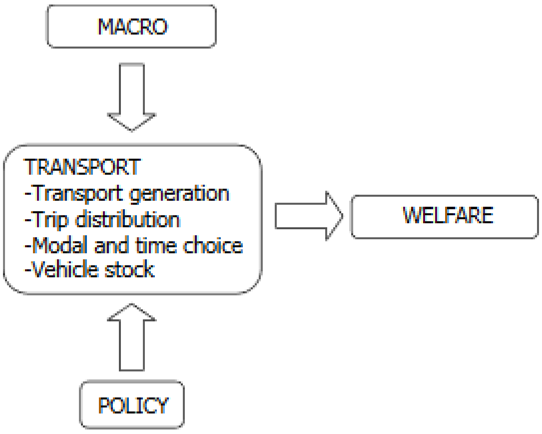
For transport modellers involved in long-term projections, these developments pose a huge challenge. Each individual development is, in itself, subject to profound uncertainties. This is especially the case beyond 2025-2030, which is usually considered as the period where, on the one hand, battery electric vehicles (BEV) will become fully competitive with ICE vehicles and, on the other hand, fully automated vehicles will be able to hit the road *en masse*. But these uncertainties are compounded by the complementarities we have just discussed, which could lead to profound and accelerating changes in our mobility systems once a "tipping" point has been reached (Franckx 2016, Fulton et al. 2017a, Arbib & Seba 2017).

1.2. Long-term transport demand projections in Belgium

The issues discussed above raise the question to what extent the models that are currently used for long-term projections of the transport system are adapted to deal with what could be the most transformative change in the transport system since the mass adoption of private cars. Moreover, transport modellers need to address which changes in the modelling approach can be implemented in a given time horizon, taking into account data availability and budget constraints.

In Belgium, national long-term projections are provided by the PLANET model (Desmet et al. 2008, Gusbin et al. 2010), which has been developed by the Belgian Federal Planning Bureau. We succinctly describe here the main building blocks of the model. It consists of seven interrelated modules: Macro, Transport Generation, Trip Distribution, Modal and Time choice, Vehicle Stock, Welfare and Policy.

The Macro module spatially disaggregates results of the macro-economic projection models HERMREG, HERMES and MALTESE to the level of NUTS3 zones in Belgium. This information is supplemented by demographic and socio-demographic projections.



The **Policy module** summarises the policy instruments that are used in the business-as-usual and alternative scenarios. These consist of transport instruments (such as fuel taxes, ownership taxes or road pricing). Moreover, it defines how additional net tax revenue generated in the transport sector is "recycled" by the public sector, or how extra revenue needs in the transport sector are financed.

The transport core of PLANET consists of four modules. The **Transport Generation** module derives the total number of passenger journeys produced in and attracted to each NUTS3 zone. In addition, it makes a projection of the total tonnes lifted for national and international freight transport. The results of this module are fed into the **Trip Distribution** module which determines the number of trips taking place between each of the zones. In the next step, the **Modal and Time** Choice module derives the modes by which the trips are made and the time at which the trips take place. These choices depend on the generalised costs[2] of the different options. Travel time for the road modes is determined endogenously, by means of the speed-flow function that gives the relationship between the average speed of the road transport modes and the road traffic levels. The Modal and Time Choice module also provides information on the environmental impacts of transport and on net government revenue obtained from transport. The environmental impacts of cars depend on the composition of the cars stock[3], which is simulated in the **Vehicle Stock** module. In each year *t* the stock of vehicles surviving from year *t-1* is compared with the desired stock of vehicles needed by the transport users. If the desired stock is larger than the surviving stock, new vehicles are bought. A calibrated nested logit model is used to estimate

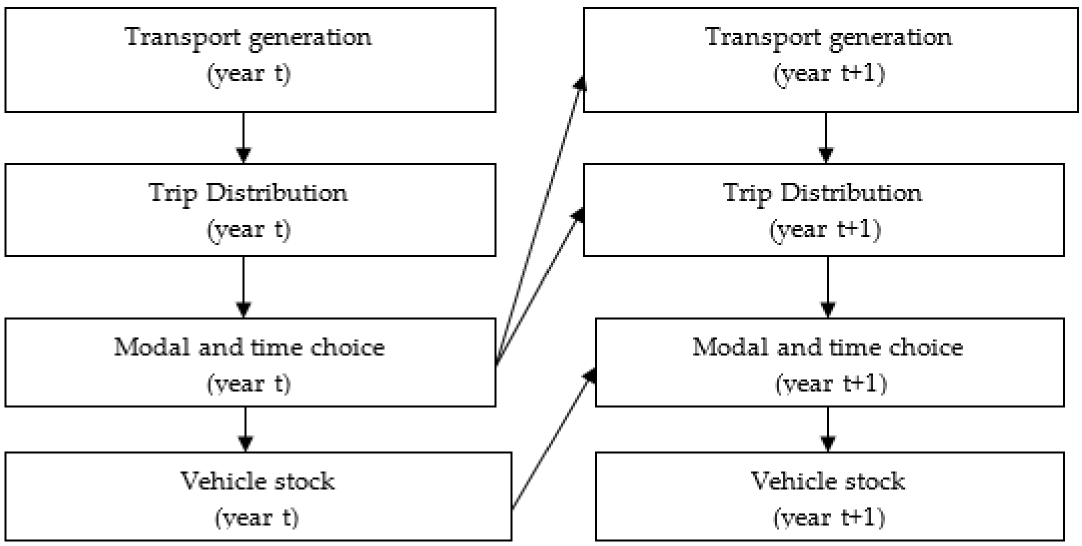
2 This refers to the sum of the financial costs and the opportunity cost of the time spent in travel.
3 For buses, road freight vehicles, inland navigation and rail the vehicle stock is not modelled. In these cases, the model uses information about the vkm and tkm rather than the vehicle stock to determine resource costs, environmental costs, etc.

the share of diesel and gasoline cars in annual purchases, while the shares of alternative fuel vehicles (AFV) evolve exogenously[4].

In summary, the transport core of PLANET is close to the approach chosen in 4-step models, except that there is no explicit assignment of the transport flows to the network.

Some of the outcomes of the four transport modules for year *t* affect transport demand in year *t +1*. First of all, the demand for passenger trips for "other" purposes and of tonnes lifted in Belgium by transit freight transport (determined in the Transport Generation module) depends on the average generalised cost of these transport flows in the previous year (determined in the Modal and Time Choice module). Secondly, the generalised transport costs resulting from the Modal and Time Choice module influence trip distribution in the next year. Finally, the composition of the road vehicle stock has an impact on the monetary costs of road transport in the next year.

The **Welfare** module computes the effects of transport policy measures on economic welfare. It produces a cost-benefit analysis of the transport policy reforms summarised in the Policy module. It takes into account the impact on the consumers' and the producers' surpluses, the government revenues and environmental externalities.



1.3. Focus of the current review

The focus of the paper is to understand how the developments described in section 1.1 should affect the vehicle stock modelling, and how this can best be dealt with in long term projections.

Several studies have explored the impact of shared and automated mobility on the car stock that is needed to satisfy mobility demand on the one hand, and on the vehicle kilometres (vkm) driven on the other hand (Burns et al. 2013, Spieser et al. 2014, ITF 2015). It turns out that this relation is complex and highly context dependent. For instance, in rural areas, people are more likely to drive long distances on

[4] In the current version of PLANET, these exogenous shares are based on Devogelaer and Gusbin (2014).

a regular basis, and shared automated vehicles are less likely to be financially advantageous compared to privately owned vehicles. At the other end of the mobility spectrum, in cities with extremely high population densities, car ownership is already relatively low, and shared automated vehicles are more likely to be substitutes for taxis than for private cars. Nevertheless, in both cases, Burns et al. (2013) show that shared and automated mobility will have a substantial impact on the size of the vehicle fleet that is needed to satisfy mobility demand. Moreover, with battery prices and performances changing more quickly than was anticipated until very recently[5], the share of electric vehicles is also likely to change more quickly than previously thought.

To be sure; other key features of transport demand are also likely to change. For instance, automated mobility is likely to result in increases in distance travelled, even if the actual number of cars decreases (Greenblatt and Shaheen 2015; Childress et al. 2015; Morrow et al. 2014). It is also expected that automated mobility will lead to longer commutes and thus to further urban sprawl (Morrow et al. 2014). The more "rational" behaviour of connected automated cars (compared to human drivers) is also likely to change the existing relations between transport volumes and speed levels[6]. Finally, shared mobility blurs the lines between individual transport and public transport, and is likely to fundamentally change the substitution possibilities between modes. These issues will be the subject of separate papers.

In what follows, we will review a broad range of car stock models that are currently used for long-term projections of (parts of) the transport system. Our objective is to take stock of the current state-of-the-art in vehicle stock modelling[7], and to better understand how the choice of a specific modelling approach is related to, *inter alia*: how other features of the transport system (such as the overall demand for transport services and the modal choice) are represented in the model, the time horizon taken, the level of technical detail that is required for the questions addressed by the model, etc.

We will limit ourselves to models that, such as PLANET, aim to assess the behavioural response of private agents to policy. We do not cover optimisation models, which have been designed to find the energy system that minimizes total discounted system cost within the limits of imposed policy and physical constraints. Neither shall we consider models that only model the size of the fleet, but not its composition.

Our review is structured as follows.

In Section 2, we address the following issue: vehicle stock models are usually embedded in a transport demand model, which can also include projections of total mobility demand, modal choices, route choices etc. The representation of the vehicle stock is usually not independent of other key choices in the design of the transport model. We therefore briefly discuss here some of the key approaches to classify transport models, and how these issues have been dealt with in PLANET.

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[5] https://www.ft.com/content/44ed7e90-3960-11e7-ac89-b01cc67cfeec Financial Times, The Big Green Bang: how renewable energy became unstoppable, 19 May 2017. https://www.ft.com/content/6e475f18-3c85-11e7-ac89-b01cc67cfeec Financial Times, Electric car costs forecast to hit parity with petrol vehicles, 19 May 2017.

[6] For a recent illustration, see Stern et al. (2017).

[7] At this stage, we only address the vehicle stock for cars. The terms "vehicle stock models" and "car ownership models" will be used interchangeably.

In Section 3, we move on to a general discussion of vehicle stock modelling. We first give an overview of the most common approaches used in vehicle stock modelling. Second, we discuss in some more detail the differences between top down and bottom up models, and the main advantages and drawbacks of both approaches. Third, we briefly explore some of the approaches that have been used to relax the restrictive behavioural assumptions underlying most 'traditional' vehicle stock models. Finally, we discuss three approaches that have been used to model the demand for vehicle types that have currently low or zero market shares, but that are expected to have an important potential in the long run.

This leads us naturally to Section 4, where we focus specifically on the problem of vehicle stock modelling in long term projections. We propose a classification of these models, and discuss their most important features – a comprehensive discussion of these models can be found in the annexes to this paper. We also discuss possible lessons for future developments of the PLANET model.

Finally, in Section 0, we summarize the key findings of the paper and propose priorities for further improvement, with a focus on the needs of the PLANET model. Our key conclusion is that the approach taken should depend on the time perspective of the model. In the short run, consumer preferences and vehicle technologies can be assumed to remain stable, and the evaluation of policies is best based on econometric models. In the long run, preferences and technologies are fundamentally uncertain, and a scenario approach is the most appropriate: instead of collecting additional data and refining our econometric forecasts, we need to explore possible futures, and outline the implications of the most extreme scenarios that still seem plausible. In between these two extreme time perspectives, there is the medium term. For medium term projections, we propose to start with existing econometric models, but enriched with models of social learning[8] and learning-by-doing[9], who represent how new technologies and business models are gradually adopted in society. Repeated simulations with random changes in the values of the key parameters will help us understand the robustness of our projections.

[8] To represent how consumers adopt new technologies and behaviours by learning from others.

[9] To represent how producers become gradually better in supplying new technologies and business models through the experience gained by selling to the early adopters.

2. Typologies of models: generalities

Vehicle stock models are usually embedded in a transport demand model, which can also include projections of total mobility demand, modal choices, route choices etc. The representation of the vehicle stock is usually not independent of other key choices in the design of the transport model. We therefore briefly discuss here some of the key approaches to classify transport models, and how these issues have been dealt with in PLANET:

– The integration of the transport model in a model of the wider economy
– The relation between overall travel demand and vehicle choice
– The treatment of indirect emissions
– The opportunity cost of time spent travelling
– The relative weight given to explicit economic modelling versus expert judgement in forecasting future mobility choices

2.1. The integration of the transport model in a model of the wider economy

Transport models differ in the extent to which the **representation of the transport system is integrated with the wider economy**. Integrated assessment models (IAMs) incorporate a "cross-sector approach to modelling global emissions reductions and other mitigation options", while sectoral models "focus solely on transport and its specific potential for emissions reductions" (Sims et al. 2014). The advantages and limitations of each approach are discussed in Sims et al. (2014), Daly et al. (2014), Kyle and Kim (2011) and Yeh et al. (2016).

The PLANET model is a sectoral demand model. Its main link with the broader economy is the Macro module, which describes the impact of wider economic developments on transport demand. PLANET is thus especially well-suited to assess policies that impact specifically on transport behaviour (such as modal shift or journey avoidance), but less to compare the effects of measures in the transport sector with the contributions that could come from other sectors, or the impact of transport policies in other sectors.

2.2. The relation between overall travel demand and vehicle choice

At least the following approaches are possible (Pietzcker et al. 2014, Yeh et al. 2016):

– ''service demand" models, where the vehicle stock is modelled as the number of vehicles that is needed to meet a given travel demand, which is estimated by:
  – Either starting with estimates of total travel demand (pkm or tkm), which are distributed over the different transport modes;
  – Or by estimating directly the demand for the individual modes.
– Start by estimating the number of vehicles, and then model how far each will travel.

The first approach is more appropriate if the modeller wants to consider the potential for modal shifts, but relies on data on travel activity that are less reliable and consistent than the data on vehicle stocks (Yeh et al. 2016).

PLANET follows the "service demand" approach, where travel demand is initially modelled for all modes, and then distributed over the modes according to a nested Constant Elasticity of Substitution (CES) function.

2.3. The treatment of indirect emissions

Across models, there are important differences in how **indirect emissions** are accounted for. Some models limit themselves to tailpipe emissions. There are at least three other dimensions to consider:

– The emissions linked to the production of the fuel, and its transportation up to the place of use. This is especially important for the evaluation of alternative fuels. In the case of biofuels, an additional question is how far one should go in accounting for (indirect) land use effects (ILUC).
– The emissions linked to the production and the disposal of vehicles, which may be important when evaluating incentives to scrap highly polluting vehicles, such as "cash-for-clunkers" schemes.
– The emissions embedded in the construction and maintenance of transport infrastructure, which is relevant to evaluate the long-term impact of measures promoting modal shifts.

In PLANET, only well-to-wheel emissions are considered – this includes tailpipe emissions and emissions due to e.g. the wear-and-tear of tyres. The emissions linked to the production of the fuels are also included, but not any ILUC of biofuel production.

2.4. The opportunity cost of time

There exist two main approaches to include the **opportunity cost of time** spent in travel in transport models: (a) translate the time cost in monetary values, so that it can be combined with the financial costs of travel to obtain the generalised cost of travel (b) impose an exogenous constraint on the daily amount of time spent in travel activity. While the latter approach has no firm basis in economic theory, it does refer to an empirical regularity (see for instance Daly et al. 2014 and Pietzcker et al. 2014) and is often used in long term projections of travel demand (Schäfer and Victor 2000).

In the long run, the limited speed of light duty vehicles, in combination with congestion, is one element that could contribute to the saturation of the demand for private motorized travel. (Pietzcker et al. 2014). As the value of time depends on the wage rate, economic growth will lead to an increased time cost of travel, and this could promote a modal shift towards high-speed modes such as air and high-speed rail. This is consistent with the observed historical trends as discussed in Schafer and Victor (1999). On the other hand, increased wages also increase the cost of service provision in the case of public transport (Kyle and Kim 2011), which will also impact modal shares – an additional element of uncertainty being that high wages in public transport could accelerate the adoption of driverless vehicles.

In PLANET, the time cost of travel is included in the generalised cost of transport.

2.5. Explicit economic modelling versus expert judgement

Across models, there is a huge variation in the extent to which they rely on **explicit economic modelling**. In some cases, future projections are based as much as possible on a rigorous economic framework (utility maximizing consumers and profit maximizing firms, model parameters estimated with econometric methods, explicit optimisation). Other models rely mainly on expert judgements for forecasting future technology and modal shares.

This distinction is not binary. As we shall see, even models that are firmly embedded in a rigorous economic approach, also rely on expert judgements for at least some model parameters.

Nevertheless, these differences in approach matter. For instance, economic models take into account parameters such as the wage rates, which affect the cost of modal shifts to public transport. As a result, economics-based IAMs (such as GCAM, see Section 4) tend to have a less favourable view of the potential for modal shift (Yeh et al. 2016).

PLANET can be considered as a hybrid model, as it combines explicit economic modelling (such as the use of CES functions for the modal choice) with simple extrapolations of historic trends (such as in the trip generation module).

2.6. Key design choices in PLANET

Summarizing, the PLANET model is a sectoral model of the transport sector. It follows the "service demand approach": it first models travel demand for all modes combined, and then allocates total demand to individual modes according to a nested CES function. It considers only well-to-wheel emissions: it does not consider the environmental effects of the production and the scrapping of vehicles, nor the damages linked to the building of the transport infrastructure. The emissions of biofuels do not account for ILUC effects. The opportunity cost of time is a term in the generalised cost of transport, and no exogenous constraints are imposed on total travel time. Some aspects of the model have firm groundings in micro-economic theory (such as the modal choice), while others are based on simple extrapolations of existing trends.

When comparing the results of PLANET with other models, it is important to keep these features in mind.

For instance, shared cars are used much more intensively than privately owned cars, and are thus likely to have a shorter lifespan. It falls outside the scope of PLANET to model the impact of shared mobility on the changes in the emissions of the car manufacturing sector as a result of a higher fleet turnover.

As a second example, take the impact of AV on the opportunity cost of time; models with a fixed travel time budget will not be able to represent the impact of automated mobility on the time spent in traffic (and thus also on longer trips and especially commutes). In PLANET, this reduced opportunity cost of time will affect the trip distribution, and the modal and time choice.

3. Car ownership modelling

In this section, we discuss car ownership models in general terms, without specific focus on long term projections. We first give an overview of the most important econometric approaches to car ownership modelling. We next discuss the differences between bottom-up and top-down approaches to technology modelling and alternative approaches to the behavioural assumptions underlying car own ownership models. Finally, we discuss at length different solutions that have been proposed for the modelling of the demand for emerging technologies. This is especially important for long-term projections: some powertrain technologies that are expected to play a major role in a few decades currently have very low market shares, and this raises the question to what extent we can rely on currently observed behaviour to understand future demand and supply.

3.1. Generalities

The National Transport Authority of Ireland (2014) has recently published a review of car ownership models, which itself builds further on de Jong et al. (2004). We briefly summarize their main points here, and refer to the original paper for more details.

– **Aggregate Time Series Models** use an S-shaped curve to describe how overall car-ownership (per capita) varies over time, as a function of income or GDP and other explanatory variables. The S-shape is based on the idea that, after a slow initial take-up of a new product, sales increases when the product becomes more established, until it reaches a saturation point. This type of evolution is typically represented with a Gompertz function. Problems with this approach include that saturation levels vary with time, and that a decrease in car ownership is excluded a priori. For examples that are not further elaborated in the current text see Dargay et al. (2007) and Wu et al. (2014).

– **Aggregate Cohort Models** are an extension of the aggregate standard time-series model where the population is segmented into age dependent cohorts, each with its own car owning characteristics, which can vary over time. For instance, within one cohort, disposable income first increases with age and subsequently decreases after retirement.

– **Aggregate Car Market Models** predict how the size *and the composition of the vehicle stock* change over time, based on a set of exogenous variables. These models can for instance be used to forecast the impact of government policies such as scrapping schemes and taxation on the car stock. However, these models are not meant to forecast ownership at the level of individual households.

– **Heuristic Simulation Models** assume "that the proportion of household income spent on transport remains constant over time, and that each household will aspire to own the most expensive car(s) that they can afford." Although this approach lacks a sound theoretical basis, some argue that it is consistent with real-world data. Note that car types can still vary across households with similar incomes, as the amounts spent on the car also depend on fuel consumption (and thus annual distance travelled).

- **Static Disaggregate Car Ownership Models** uses "discrete choice models to determine the number of cars owned by individual households"[10]. One drawback of this approach is that aggregating individual household choices can lead to global results that are not consistent with the saturation hypothesis. This can be remedied by using aggregate models to forecast the total number of vehicles, and to use the choice models to disaggregate total car ownership.
- **Indirect Utility Car Ownership and Use Models** consider the relationship between car ownership and car use as a single decision problem for the households. The main disadvantage of this approach is that it increases the complexity of the models and is fairly data intensive. The advantage is that it acknowledges that the type of car purchased can depend on the expected annual distance travelled.
- **Static Disaggregate Car Type Choice Models** consider the type of car (and not just the number) owned by different households.
- **Panel models** use data collected over time from the same group or "panel" of respondents. In the case of pseudo panels, the composition of the group may vary. These models are useful to understand dynamics, such as for instance possible time lags between causes and effects, but are very data intensive. One recent example of using is Klein and Smart (2017), who use the US Panel Study of Income Dynamics (PSID) to examine recent changes in auto ownership among US families, with a particular focus on Millennials. An example of the use of repeated cross-sectional data to examine the same issue (mobility behaviour of Millennials) is Garikapati et al. (2016).
- **Dynamic Car Transaction Models** consider "how car ownership of individual households change over time, by considering the factors that influence whether a household acquires or disposes of a vehicle". The main drawbacks of this approach are the high complexity and the data requirements.

We can classify these models according to the following dimensions: (a) whether they aim to predict the number of cars only, or also the composition of the fleet (b) whether they produce projections at the aggregate level or at the level of individual households. In order to provide a useful input to emission models, it is necessary to have projections of both the size and the composition of the car stock.

Table 1 Classification of car ownership models

	Aggregate level	Household level
Number of cars	Aggregate Time Series Model, Aggregate Cohort Models	Static Disaggregate Car Ownership Models
Composition	Aggregate Car Market Models	Heuristic Simulation Models, Indirect Utility Car Ownership and Use Models, Static Disaggregate Car Type Choice Models, Dynamic Car Transaction Models
Numbers and/or composition		Panel models

In the PLANET model, the total number of cars is determined at the aggregate level: it is the number of cars that is needed to meet the expected mobility demand, as expressed in the number of vehicle km calculated in the trip distribution model. However, the split of aggregate demand over individual vehicle classes and the expected mileage are determined in a calibrated Indirect Utility Car Ownership and

[10] A recent example of this approach is the National Car Ownership Model (NATCOP) used in the UK (Department for Transport, 2016).

Use Models[11]. No attempt is made to estimate the number of cars per household[12]. In short, PLANET is an aggregate model of the car stock composition.

3.2. Top down versus bottom up models

The next issue is how transport models (or the models of the energy sector in which they are embedded) represent individual technologies, where in the case of cars, "technologies" usually refers to the power-train of the car.

In **bottom-up approaches**[13] (Rivers and Jaccard 2005, Horne et al. 2005, McCollum et al. 2016a), individual technologies are represented in detail, and this allows for an explicit modelisation of changes in the technology mix. Market shares of abatement technologies are based on the technologies' financial costs and the social discount rate only. These models usually assume homogeneous end-users making perfectly rational decisions.

Their main drawbacks and limitations are (Rivers and Jaccard 2005, Horne et al. 2005, McCollum et al. 2016a, Schafer 2012):

– The adoption of new technologies implies uncertainties and risks for consumers and firms that are not always adequately represented by the social discount rate. Moreover, consumers and firms can gain by postponing investments until more information has become available.

– Even if enough information is available to appraise the risks, the costs and the benefits linked to a technology, gathering and synthetizing information about technologies is costly, and may therefore not be undertaken.

– These models do not represent the heterogeneity of consumers and firms, and therefore hide that some technologies are not cost-effective for some subgroups of the entire population of potential adopters. Moreover, two technologies that are similar according to the features included in the model, may be perceived as different by the users.

– The adoption costs of technologies are not always represented accurately.

– They usually rely on exogenous trends of transportation demands and modal choices.

As a result; bottom-up models tend to be too optimistic with respect to the potential for low-cost reductions in emissions linked to energy use, but do not consider the potential of behaviour changes such as reductions in transport demand and/or modal shifts (see Daly et al. 2014 and Pietzcker et al. 2014).

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11 As discussed in Section 1.2, the shares of conventional fuels (diesel and gasoline) are calculated in a nested logit model, while the (evolving) shares of AFV are imposed exogenously. Annual mileage depends on income and on the monetary variable costs, which vary according to fuel type and car size.

12 Although this can be deduced from the model outputs.

13 The term "bottom-up" models is also sometimes used to refer to detailed regional and local transport models, who treat the wider transport sector as given. 4- stage transport models are a typical example (Stephenson and Zheng 2013). However, these are clearly two distinct concepts.

One approach that has been used to deal with the limitations of bottom-up models is to use discount rates that are higher than the market rates, and to allow these discount rates to vary across end users. Other models[14] explicitly include elements such as market heterogeneity, intangible costs and benefits.

Bottom-up transport models often use an exogenous, fixed time travel budget (Kyle and Kim 2011, Girod et al. 2013b) – as discussed above, this assumption is based on an empirical regularity rather than on micro-economic theory.

In **top-down models**, the overall economic effect of a policy is based on aggregated market data. They are based on observed behaviour, but face challenges of their own (McCollum et al. 2016a, Horne et al. 2005, Stephenson and Zheng 2013):

– Because the top-down models assume that observed market behaviour results from the interaction between optimizing agents, they implicitly assume that the current technology mix is already (close to) optimal. Any deviation from this equilibrium would then entail important costs.
– More specifically, top-down models struggle with the issue of technological change. The key parameters in these models are: (a) the elasticities of substitution, which define how easily one aggregate input can be substituted for another as their relative prices change, (b) the autonomous energy efficiency index, which defines how quickly energy efficiency increases autonomously in the economy. Estimates of these parameters are usually based on historical data, and will not necessarily remain valid in the future. This is especially the case for emerging technologies where economies of scale or learning-by-doing could lead to dramatic *endogenous* cost decreases in the future. Thus, top-down analysis has problems in capturing technological change, which is especially important in long-term projections.
– Although a lot of work has been done to endogenize technological change in top-down models, the empirical aspects remain problematic. Moreover, historical adoption behaviour with respect to new technology is not necessarily representative for the way consumers will deal with currently unknown technologies. We will discuss the representation of spill overs and learning effects in more detail in Section 3.4.
– The high level of aggregation is not adequate for an analysis of policies that are technology-oriented such as regulations of technologies. The analysis of this type of regulation requires a more detailed representation of technologies. From a policy point of view, this is especially problematic, as policy makers tend to be more interested in technology-oriented instruments than in economic instruments.

As a result, top-down models tend to overestimate the costs of environmental policies and are not well equipped to deal with the issues that policy makers are most interested in.

Modellers have worked on approaches to deal with the shortcoming of both type of models. As a result, so-called 'hybrid' models are emerging, which are blurring the line between the two approaches (Horne et al. 2005).

[14] Such as BLUE – the Behaviour Lifestyles and Uncertainty Energy model for the UK – see Lia and Strachana 2017

In PLANET, the modal and time choice are represented with a nested CES function. For individual modes, the level of technical detail varies. It is only for passenger cars that the demand is explicitly modelled, up to the level of the market segments used in the COPERT methodology[15]. PLANET can therefore be placed in the category of hybrid models. For long-term projections, there is a strong need to explicitly represent processes of technological change in the vehicle stock, which is currently missing.

3.3. Representation of behaviour

As discussed above, 'traditional' bottom-up and 'top-down models both often impose restrictive behavioural assumptions of consumer homogeneity and rationality. Several deviations from these assumptions are possible (McCollum et al. 2016a):

– Modellers can assume that economic agents have limited rather than perfect foresight, that they use non-optimising heuristics[16] etc.

– Instead of working with 'representative agents', modellers can account for heterogeneity. For instance, end users may differ in how they perceive using non-motorized modes.

– Modellers can explicitly represent social influences and contextual[17] conditions.

In a recent review of the literature on IAMs, McCollum et al. (2016a) conclude that the "current modeling of behavioral features in global IAMs is relatively limited and quite varied". When heterogeneous agents and nonmonetary preferences are represented at all in IAMs, this is typically with the use of multinomial logit functions (MNL), for instance of vehicle choice.

In PLANET, the aggregate demand for cars is split in the demand for broad categories of "car types" according to a calibrated nested logit function, which does not account for individual household characteristics.

3.4. Emerging vehicle technologies

One possible approach to estimate peoples' preferences for specific transport choices[18] is to use **revealed preference** data (RP). In this case, the data pertain to actual choices made in real markets. RP surveys ask people about their actual purchases made, and about the key socio-economic characteristics of their households. The measured attributes of the purchased goods[19] (and of the goods that were not purchased) then inform us about the underlying preferences of consumers[20].

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15 COPERT is a software tool used to calculate air pollutant and greenhouse gas emissions from road transport. COPERT has been developed for official road transport emission inventory preparation in member countries of the European Environment Agency.

16 For instance, sticking with current car ownership and use patterns, even when better alternatives are available.

17 For instance, the availability of refuelling infrastructure or the accessibility of public transit.

18 Such as modal choices or car models.

19 For instance, in the case of cars, their price, their power, their autonomy, their size, their luggage space, their fuel consumption, etc.

20 See Train (2001, p. 174).

The use of RP surveys in long term projections is not without its problems. One important issue[21] is how to estimate the demand for new or emerging technologies, who currently have low or even zero market shares. This raises at least the following issues for RP:

- If the technology is already available on the market, then the revealed preferences of the early adopters may not be representative of those of the population as a whole. For instance, these early adopters may have strong pro-environment preferences or be very keen on new technologies (Richardson et al. 1999, AECOM Australia 2009).
- If the technology is not yet marketed, the modeller may use the estimates for a surrogate technology, but such a surrogate is not always available (Richardson et al. 1999).
- In order to deal with the unavailability of market data pertaining to the demand for alternative fuel vehicles, one may estimate the implicit price of the *attributes* of vehicles instead. This hedonic pricing approach is feasible if one can rely on historical data with respect to these attributes. For instance, Walls (1996) has used hedonic pricing to estimate the cost of using Compressed Natural Gas (CNG) vehicles, which differ from gasoline vehicles according to attributes (fuel efficiency and tank size) whose value can be estimated. However, this approach cannot be used for large changes in the attributes (Richardson et al. 1999).
- One can compare the Total Cost of Ownership (TCO) of new technologies with those of established ones, and assign the demand to the minimal costs technology. An important advantage of this approach is that it relies mostly on data that are available. However, it omits non-monetary attributes, which are known to be important in car choices (such as the car's performance). In the case of alternative fuel vehicle (AFVs), non-monetary attributes such as the range and the availability of a charging infrastructure can even be the key barriers to adoption. Moreover, calculating the TCO requires discounting of future costs such as the operating costs, and there is ample evidence that people use (irrationally) high discount rates when purchasing cars – see Greene (2010a,b). Finally, using the TCO as sole decision criterium does not take into account consumers' heterogeneity (Massiani 2013).
- Diffusion theory represents the progressive diffusion of a technology from a given observed level to a hypothesized potential. For instance, the Bass approach postulates that new technologies have a given potential which will be reached progressively, starting from the introduction phase. (Massiani 2013), thus following a sigmoid function. Although there are examples of applications of Bass diffusion theory to AFV, a major limitation of this approach is that many factors affecting the market share are ignored (Liu and Lin 2017). Kolli (2012) is a relatively recent application of this approach to the diffusion of AFV in France. Interestingly, Kolli emphasizes that it is difficult to forecast the future diffusion of AFV, given their currently very low marking shares and other factors, such as the increasing longevity of car models of all categories. As a result, the "potential" of AFV used in the model represents more a value judgement (the share that is desirable at some point in the future) than as assessment of the future potential, given current market behaviour. In Kolli's approach; even the future shares of diesel and gasoline cars are based on exogenous assumptions.

[21] Another one is that it is debatable whether RP data collected today are representative for consumer preferences 20 years from now.

Instead of using RP data, one may use discrete choice experiments using stated preferences (SP) to estimate the value of non-monetary attributes of new, unfamiliar vehicles (such as range and refilling time) (McCollum et al. 2016a). This approach can be summarized as follows: “Stated-preference data are data collected in experimental or survey situations where respondents are presented with hypothetical choice situations. The term ‘stated-preference’ denotes the fact that the respondents state what their choices would be in the hypothetical situations. For example, in a survey, a person might be presented with three cars with different prices and other attributes. The person is asked which of the three cars he would buy if offered only these three cars in the real world. The answer the person gives is the person’s stated choice.” (Train 2001, p. 174).

Given the important role played by SP studies in the analysis of AFV, we further elaborate on them here.

a. Stated Preference surveys of vehicle choice

Besides their ability to deal with new or currently unavailable technologies, other advantages of SP surveys are that (a) for a given budget, they can generate larger datasets than RP studies (b) contrary to TCO models, they allow the inclusion of non-monetary features and of consumer heterogeneity (c) they allow a simulation of the context that represents the policy question (d) the researcher decides which attributes to include in the study (see for instance Massiani 2012). The main drawback of SP is that they have no real-world financial implications for the respondents, and thus that they suffer from so-called ‘hypothetical bias’ (Massiani 2013). Another important limitation is that they are often used to estimate the demand for products and services that the respondents are not familiar with. One can question whether there is anything ‘rational’ about preferences that are expressed in this way.

Wilson et al. (2014) have undertaken a literature review of 16 discrete choice studies of alternative fuel vehicles. Comparing the results of these models is not straightforward, as they often differ with respect to “both the assumptions made about the distribution of unobserved utility and the independence of choice alternatives”. Another important cause of variation between study are the AFV that are included in the choice set. As discussed by Massiani (2014), not considering the full range of AFV is not innocuous. The share of BEV may for instance be different if the choice sets excludes FCEV. Also, some technologies (such as PHEV) can be considered to be transition technologies on the road to BEV[22].

Attributes that are commonly included in the studies are: the purchase price, operating costs (including fuel), the vehicle range, the size of the vehicle, the engine power, indicators of safety and reliability, the availability of a refuelling infrastructure and a service network, recharging time of batteries, and sometimes environmental performance.

There is some discussion whether all financial costs should be considered as a single variable, and thus whether the fixed costs should be ‘annualised’ using the market discount rate. As discussed above; there is serious evidence that people use higher than market rates when discounting future costs of automo-

[22] Massiani (2014) also raises the question whether transition technologies should be included explicitly, or whether it is enough to represent them by the features that make up the utility function. We refer to Massiani (2014) for an extensive discussion.

bile use. Hence, a convincing case can be made that fixed and variable costs should be considered separately. It would also reduce cognitive burdens for the respondents if fuel efficiency would be expressed directly in monetary terms rather than in physical ones (Massiani 2014).

Researchers face a trade-off between the cognitive burdens imposed by a longer list of attributes, and the realisation that the omission of some attributes can seriously bias the outcomes. For instance, when facing higher fuel prices, people can respond by switching to AFV, but also to a smaller conventional car. It could thus be that some small conventional vehicles are closer substitutes for large conventional vehicles than AFV. Omitting the size and the power of the car can thus misrepresent behavioural responses (Massiani 2014). Typically, SP studies include at the most 6 attributes (Wilson et al. 2014).

Some studies also include indicators of consumer heterogeneity. Differences between consumers can be directly observable (income, age, gender, household composition, and education) but also reflect differences in value systems (attitudes to travel, environmental preferences and technological awareness, for instance), which are not. Factor analysis and latent class analysis can be used to group individuals according to common traits (Wilson et al. 2014).

Wilson et al. (2014) conclude that social and contextual influences are consistently found to be important determinants of vehicle choice. These influences can result from the information people receive from their peers or from peer pressure. However, they may also simply reflect that "two people who are neighbours, friends or family members are likely to be subjected to similar contexts that influence their decisions", such as for instance the available transport infrastructure. The study of social influences is thus plagued by identification problems.

Other contextual factors that can matter is that the relevant features may differ, depending on whether or not the household is purchasing a first or a second car. For instance, a second car may differ in its required size and usage intensity compared to the first car owned by the household. For AFV, owning a garage (with charging facilities) is also an important factor affecting the convenience of BEV. Travel needs may also vary, depending on whether one lives in an urban, suburban or rural area. These elements are often missing in SP surveys (Massiani 2014).

In most studies surveyed by Wilson et al., the overall model fit was rather poor (McFadden's R2 in the region of 0.15 – 0.17). This indicates that relevant explanatory variables are missing from most studies (Wilson et al. 2014). According to Massiani (2014), the choice of features to include in SP surveys has received insufficient attention compared to other modelling issues such as the structure of correlations between error terms in the discrete choice models. For instance, the environmental performance of AFV is sometimes included as explanatory variable, but Massiani argues that it is doubtful that people understand its full meaning. Moreover, in SP surveys, parameters for this variable could essentially reflect a "warm glow" effect.

b. The Synthetic Utility Function approach

Massiani (2013) has argued that, because of the limited number of attributes that can be included in a single SP survey, and the sensitivity of the model results to the idiosyncrasies of the survey design, relying on a single SP survey would yield non- robust results and/or policy recommendations. Instead, Massiani proposes to proceed with a Synthetic Utility Function. In this approach, the willingness-to-pay (WTP) for individual features is estimated, using a broad range of existing studies. This would make the estimates less dependent on the specific design of an individual survey, would allow the researchers to include a broader range of feature than what is possible in an individual study, and include information obtained from other data sources, such as RP studies.

Massiani illustrates how this approach can be used to estimate the WTP for various attributes, such as: the range of the vehicles, refuelling stations network, car performance (expressed in terms of horsepower or acceleration time or maximum speed), operating costs, emissions, alternative specific constant and (the lack of) diversity (number of models available in one technology). These WTP can then be integrated in a Synthetic Utility Function.

Other examples of this synthetic utility approach are scarce. AECOM Australia (2009) have used this approach, together with long term projections of the features included in the model, to perform long term projections.

A similar, and older, example is the Transitional Alternative Fuels and Vehicles (TAFV) Model, a nested multinomial logit (NMNL) model which has been considered a pioneering approach in modelling the adoption of alternative fuel vehicles (Liu and Lin 2017). Instead of relying on SP surveys, its coefficients are based on "basic economic assumptions" or "consensus estimates of the marginal values of attributes" (Greene 2001). According to Greene, such estimates do not suffer from the main drawbacks of SP surveys: (a) the tendency for respondents to underestimate their true sensitivity to market prices, and (b) the inability of respondents to consistently make trade-offs among a large number of attributes. The model assumes identical consumers (up to the random utility factor). In other words, purchasing behaviour is not assumed to depend on socio-economic characteristics.

MA3T is a further development of the TAFV, but as it also includes some innovative features, we discuss it in more detail in Section 7.2.a.

There are several specific challenges with the use of Synthetic Utility Functions, most of which are discussed in Massiani (2013, 2014):

- In some cases (such as for instance the vehicle's range), one would expect non-linear relations, but most published estimates only report linear values.
- Some attributes (such as the vehicle's range and the density of the refuelling network) are likely to interact.
- The quality of the refuelling network depends not only on its density, but also on the speed of refuelling. The speed of refuelling is however not always specified in existing work, and it can be doubted that interviewees fully understand the significance of refuelling speed for EV range.
- In the case of Hybrids, the battery capacity is not a bottleneck in the vehicle's range, as it is for BEV (see Greene 2001).
- For any given market segment, diversity has a value in itself, as it increases the likelihood that a model is available that is close to the consumers' 'ideal' choice in terms of unobserved attributes (see also Greene 2001 and McFadden 1978).

- It is up to the researchers to decide the nesting structure to use for the synthetic utility function. For instance, for reasons of transparency and to make communication with stakeholders simple, AECOM Australia (2009) have used a simple multinomial logit model. However, as the nesting parameters reflect a similarity between the available alternatives that are not measured with the attributes that have been included, other choices may be more appropriate, for instance starting with vehicle size in the highest nest, and fuel type in a lower nest (Gosh et al 2015).

One topic that merits some more discussion is the use of Alternative Specific Constants (ASC) of the MNL. As it is impossible to identify all the features that affect the utility of a technology, the ASC reflect the influence of attributes that have not been included (Wilson et al. 2014 and Liu and Lin 2017). The inclusion of additional attributes should lead to smaller values of the ASCs (Massiani 2013).

In SP preference surveys, ASC are sometimes used to calibrate the model if predicted market shares deviate too much from observed market shares. However, this method cannot be used for AFVs that are currently not available at all. For vehicles with very low market shares, the AFV is also very sensitive to the assumed probability distribution for the error term in the utility function and to the lack in diversity in this market segment (Massiani 2014).

c. Joint use of SP and RP data

One particularly interesting issue raised in Axsen et al. (2009) is that the joint use of SP and RP data to estimate choice models can combine the specific strengths of RP data[23] and SP data[24].

In the deterministic terms of the random utility function, the attribute coefficients (β) represent the trade-offs between the attributes while the alternative specific constant terms (α) represent utility that is not captured in the β vector. Therefore, the α are responsible for calibrating RP models to fit observed market shares. This understanding leads to the consideration of the following two approaches:

- In the data ‘’pooling’’ approach, SP and RP data are combined to estimate the β vector (the attribute coefficients) from both sources (β^{Joint}) – where RP and SP influence can be weighted differently – while the alternative specific constant terms α is estimated from the RP data only (α^{RP}).
- The ‘’sequential’’ approach estimates separate SP and RP models, then discards α^{SP} and the β^{RP} vector. The β^{SP} vector and α^{RP} are placed in a composite utility function, where α^{RP} is recalibrated to fit the real-life market shares represented in the RP data. This approach may be preferred if RP suffer from multicollinearity.

When coefficients from different discrete choice models are integrated, one must take into account that, across models, the scale in observable utility (β and α estimates) relative to unobservable utility (ε_j) may be different – see Train (1993, 2002). As RP cannot hold the non-specified attributes constant, Axsen et al. argue that their ε_j variance will be larger. We refer to the original paper for a detailed discussion of how they have dealt with this complication.

23 The realistically accounting for income and supply constraints.

24 The better representation of hypothetical market conditions and the elimination of problems of multicollinearity.

For their topic of analysis, Axsen et al. found that SP models provided realistic and empirically consistent trade-off coefficients (β), such as capital cost, fuel cost and performance, but yielded overly optimistic HEV market share predictions. On the other hand, RP models were better calibrated to actual vehicle market shares, but β coefficients appeared to be unreliable due to multicollinearity. They found that joint modeling techniques generally improved upon models using only SP or RP data, and that the ''sequential'' technique performed best of the joint methods explored (at least in the context of their model).

4. Vehicle stock modelling in long term projections

We now move to the key topic of this paper: how vehicle stocks are represented in long term transport projections. A more extensive discussion of these models can be found in Annex, including full references to the sources that were consulted. We have grouped the models according to the approach used for modelling the annual sales of vehicles.

Table 2 describes models where the **annual sales of vehicles** are the **"residual" variable**. In concrete terms, this means that:

– The existing stock of vehicles is retired according to a scrappage function. Usually, this is a simple extrapolation of past scrapping behaviour or based on an S-shaped survival curve (a Gompertz or a Weibull distribution). However, there are also models where scrappage is based on an explicit economic calculation.

– The total vehicle stock is estimated. One common approach is to calculate the stock that is *needed* to meet travel demand (expressed in pkm). This calculation requires the following steps: (a) translate travel demand expressed in pkm in travel demand expressed in vkm (b) divide total vkm demand by the annual distance travelled per cars in the existing stock. This step thus requires values for the load factors and the average vkm for existing vehicles, which are usually exogenous and calibrated on historical data. However, there are several alternative approaches – see below.

– The annual vehicles sales are calculated as the desired car stock minus the actual car stock inherited from previous vintages.

– Total sales are split in classes (e.g. according to fuel or vehicle size) using a discrete choice function.

In principle, this approach is well grounded in economic theory. Modellers should however keep in mind that, in reality, load factors are not strictly exogenous. Policy measures that increase the cost of travelling alone (such as the HOV/HOT lanes[25] used in the US) or that reduce the cost of sharing rides (such as promoting carpooling apps) may lead to changes in the load factors. The growing importance of business models that consist in providing cheap and convenient "shared rides" can lead to the emergence of new modes, that are, technically speaking, cars, but with load factors that are different from private cars. How this should be dealt with, is highly model-dependent.

Similarly, it is disputable that the annual mileage of cars will remain constant if the demand for pkm increases, and that this increase in pkm will translate only in an increase in car sales. It is likely that part of the increase in pkm will lead to an increase in the annual mileage of existing cars instead. Moreover, with the increasing importance of shared cars, annual mileages will increase, even if the demand for pkm remains unchanged. This increase in the annual mileage will in turn affect the economic life of cars,

[25] The US Federal Highway Administration defines high-occupancy vehicle lanes (HOV lane) as "reserved for vehicles with a driver and one or more passengers (…) HOV lanes were originally conceived as a means to encourage carpooling". See https://ops.fhwa.dot.gov/publications/fhwahop09029/sec1_introduction.htm. In the case of high-occupancy toll lanes (or HOT lanes), the road administration "sell excess capacity to users not permitted in the lanes but who would be willing to pay for the travel time savings these lanes provide" (https://ops.fhwa.dot.gov/publications/fhwahop09029/sec4_policy.htm). Another way to put this, is to see HOT lanes as lanes subject to a toll, but where the driver gets exempted if he takes passengers with him.

and thus also scrappage rates[26]. Similarly, it is known that usage patterns of company cars differ from those of privately owned cars (Gutiérrez-i-Puigarnau & Van Ommeren, 2011), and thus that the average mileage of the car stock will depend on the share of company cars in the total vehicle stock. Here as well, there is no "one size fits all" solution for all models.

Compared to the approach described above, several models use a slightly different approach to estimate the total vehicle stock. The most common alternative is to **model the demand for the stock directly**, rather than as derived from a demand for mobility. When an econometric approach is used, demand can be calculated at the aggregate level (Hennessy and Tol 2011), or using discrete choice models at the household level (DYNAMO, New Zealand NLTDM). Some examples of this approach are:

– The Institute for Prospective Technological Studies of the EC's Joint Research Centre has developed a transport technologies model (henceforth "the IPTS model"), in which the per capita demand for ownership follows a *calibrated* Gompertz function of GDP per capita.
– In the UK Transport Carbon Model (UKTCM), the vehicle stock is estimated with a household-level demand curve for the number of vehicles. The model imposes a saturation point for the number of vehicles per household, which depends on variables such as the people below legal driving age, the household size, the parking availability (only applied to households in urban areas), and the availability of public transport (for households in non-urban areas). Hennessy and Tol (2011) impose an exogenous saturation point for the size of the car stock.

One apparent advantage of modelling the demand for the car stock directly is that it is less demanding in terms of data and behavioural assumptions: one does not need the load factors or the annual mileage of the existing vehicle stock to derive the car stock. However, this somewhat sidesteps an important feature of vehicle demand: it is fundamentally a derived demand, which follows from mobility demand as expressed in the annual pkm. Moreover, historical observations of the total car stock are compatible with different combinations of load factors and vehicle usage patterns. Therefore, there is no compelling reason to assume that past observations of, for instance, the relation between GDP and the total vehicle stock will remain stable in the future. This approach should therefore be considered as a fall-back option if the data do not allow a calculation of annual sales as residual variable.

A third possibility is to take a **baseline scenario from another model, and to derive the vehicle stock in each policy scenario as a change compared to the baseline**. For instance, in the SULTAN model, the vehicle stock in future years is modelled as a percentage change compared to the stock in the BAU scenario. Both the total stock and its composition in the BAU are calculated[27] from TREMOVE data (see further for more info on TREMOVE). When TREMOVE data were missing, other data sources were used, mainly from the ExTREMIS or MARKAL models. Another example of this approach is the SERAPIS model, where the number of vehicles in a scenario in each year is based on a linear elasticity model which modifies the number of vehicles relative to a baseline scenario[28].

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[26] CHEN and NIEMEIER (2005) provide an example of a model where the survival rate of a car depends on its accumulated mileage.

[27] In most cases, this involved an aggregation of TREMOVE data. To obtain projections beyond the time horizon of TREMOVE, simple extrapolations were used.

[28] The elasticity is based on values in the literature, but we have found no publicly available documentation of the baseline.

There are also various methods used to obtain the **parameters of the logit model** that is used to split total **vehicle sales** in categories.

One possibility is to calibrate the parameters of the discrete choice model using values from the literature, or to match observed choices with the model predictions (GCAM, UKTCM, SERAPIS, SULTAN, TREMOVE). Alternatively, the discrete choice model can be estimated econometrically. The combined use of RP-SP data is a possible approach to deal with the absence of market data for AFV (DYNAMO). Alternatively, one can assume constant shares of diesel and petrol vehicles, and predict the future evolution of AFVs using logistic growth curves and exogenous assumptions regarding the developments in the long run (New Zealand NLTDM).

There are also models that are highly idiosyncratic. In the IPTS transport technologies model, it is initially assumed that there are no capacity constraints in the production of specific vehicle types, and each market segment is allocated its "a-priori" share following a Weibull distribution with the adjusted user cost for each technology as input. After this first round, it is possible that, for a given technology, the modelled demand exceeds the supply capacities. In a second stage, the so-called *Wood* algorithm then allocates demand by priority to the most attractive technologies. We refer to the full documentation for more details on this allocation mechanism. In MINIMA-SUD, the shares for individual technologies in a given age cohort depend on a 'maturity factor' and the annualised real travel costs. The values of the 'maturity factor' are obtained through an observation of past trends and *expert judgement*. In the CIMS model, the market shares of new sales are based on a formula that represents market heterogeneity, and that is formally quite close to logit models (see Section 0 for a more detailed explanation). In practice, the parameters are now *estimated* with logit models that include neighbourhood effects[29]. In Hennessy and Tol (2011), the share of diesel car is *calculated* with a breakeven distance methodology, using historical data. In the policy scenarios, the shares of electric vehicles are *imposed*.

Amongst the approaches used for the **scrappage function**, one noteworthy point is that the current version of TREMOVE[30] allows for premature scrapping of a vehicle (on top of 'normal' scrapping, which is represented using a Weibull reliability function) – this occurs when the fixed and variable operating costs are higher than total costs (including annuity payment for capital) of a new vehicle.

Table 2 summarizes the key elements of the models we have analysed for the purpose of this survey:

- Travel demand: does the model contain a module for estimating total travel demand, expressed in pkm, tkm and/or vkm? How has future travel demand been projected?
- If the model is multimodal, is the activity per mode obtained by splitting the total travel demand or is it estimated directly from exogenous variables?
- How are changes in the vehicle stock modelled?
- How do the models represent the future demand and supply for AFV? Are future changes based on existing econometric evidence, on expert judgement, or a combination of both?
- The time horizon of the model

[29] Axsen et al. (2009 explain that the ''neighbor effect" represents the tendency for the social costs of switching to a new technology to decrease as the adoption rate increases due to changes in social concerns, increased credibility, and learning from others with more experience, as well as education, marketing and shifts in cultural norms.

[30] The PRIMES-TREMOVE version (E3MLab 2013-2014).

Table 2 Models with annual vehicle sales as 'residual' variable

Model	Travel demand	Modal split	Vehicle stock	Treatment of AFV	Time Horizon
Global Change Assessment Model (GCAM) family	Travel demand is projected at an aggregate level across all modes, size classes, and technologies. It depends on: (a) per-capita GDP (b) the generalized user cost aggregated across all modes, size classes, and technologies (c) the population. In POLES, future mobility is capped by exogenous regional saturation levels and demand is estimated at the level of individual modes. In TIMER, money and time budgets are used as exogenous input to adjust total travel demand	In GCAM, the market shares of the transport modes, size classes, and technologies in total travel demand are determined according to a *calibrated* logit formulation. The time cost of transport is a function of the wage rate – increasing incomes therefore induce a switch to "faster modes". Congestion remains exogenous. In POLES, the equation for transport demand represents the demand for the single modes. In TIMER, money and time budget are used as exogenous input to adjust mode split.	Load factor and annual mileage per vehicle are exogenous. Scrappage rates are based on historical data.	In GCAM and TIMER, the shares of AFV are obtained with calibrated logit functions. In POLES, for new road vehicles, a MNL *simulation* allocates the market shares of vehicle types and fuels as a function of life cycle costs and the availability of infrastructure such as refuelling stations	2095
IPTS	No	Cars only	Demand for ownership is estimated directly. Demand and supply are matched with the Wood algorithm.	Based on projections by industry experts.	2020
UKTCM	Econometric estimate per mode; varies by vehicle technology and age.	Can be calculated endogenously either with a demand function based on econometric estimates or imposed for user-defined policy scenarios.	The vehicle stock is estimated with a household-level demand curve for the number of vehicles. Composition is based on logit model.	In the old version of the model, for alternative fuelled vehicles, a logistic function represents adoption over time, with expected market share "at maturity" imposed on basis of expert judgement. In the new version, a choice model was developed with consumer segments based on attitudes, represented by different ASC.	2050
SULTAN	Calculated from TREMOVE data or from ExTREMIS data	Calculated from TREMOVE data or from ExTREMIS data	Modelled as a percentage change compared to the stock in the BAU scenario	Capital cost decreases according to technology specific exogenous learning rates.	2050
MINIMA-SUD	The main drivers of pkm and tkm are demographic, macroeconomic and energy price variables on the one hand, and the *generalised* costs of transport on the other hand.	Estimated according to a *calibrated* nested CES function	Obtained from the estimated demand for pkm/tkm combined with assumptions with respect to the annual mileage per vehicle and load factors. The shares for individual technologies in a given age cohort depend on a 'maturity factor' and the annualised real travel costs	The maturity factors are calculated through a combination of *extrapolations* of past developments and *expert knowledge* on the future evolution of these shares.	2030

Model	Travel demand	Modal split	Vehicle stock	Treatment of AFV	Time Horizon
CIMS	The forecast for service demand can be exogenous or the result from the interplay of the energy supply-demand module with a simplified macro-economic module.	Estimated with logit model	Scrappage of the existing stock is partly based on historical trends, partly endogenous. The load factor and the annual distance driven per vehicle are assumed constant. The output capacity of the surviving stocks is subtracted from demand in that year to calculate how much new stock must be acquired. Market shares of individual technologies in new sales are based on a logit-like formula.	The alternative specific constants (ASC) were chosen to reflect differences in vehicle types.	2035
New Zealand NLTDM	The projections of vkm travelled were based on the historical average vkm travelled per vehicle, by vehicle type and age	The vkm for public transport and private cars were estimated directly for each mode.	Scrappage rates were projected for each vehicle type in a deterministic fashion based on past scrappage rates. The number of vehicles newly entering the fleet, whether new or used, was then modelled as a function of replacement demand for a particular class of vehicle plus additional demand to meet growing demand. Occupancy rates are region specific but do not change over time.	The share of newly registered vehicles that were AFVs is based on logistic growth curves and *exogenous* assumptions about the shares of registrations in the long term. Exogenous assumptions are used to split AFV in electric vehicles and plug-in hybrids.	up to 30 years
Hennessy and Tol	Forecasts for distance travelled given per car type (engine size and fuel).	The model only considers cars.	The total car stock per capita is modelled as a function of GDP per capita.	The model cannot predict what type of conventional vehicles are replaced by AFV. Scenarios are run for different assumptions.	2025
SERAPIS (Austria)	Not documented	Car-only model	The number of vehicles is based on a linear elasticity model which modifies the number of vehicles relative to a baseline scenario.	The logit model used to estimate the share of technologies is based on Greene (2001).	2030
DYNAMO	The model determines the km driven, the average km driven per household and km driven per car type according to exogenous variables.	When used in isolation (without link to the Dutch national and regional traffic models), cars only.	A nested logit model is used to estimate the number of cars per household.	The ASC are modified through time to represent that AFVs “converge” to ICE vehicles.	2030
TREMOVE	The demand module of the model yields the demand for vkm in a given year. The annual mileage of vehicles depends on both type and age, as the economic cost of using a vehicle increases with age	According to a calibrated nested CES function	The current version of TREMOVE allows for premature scrapping of a vehicle (on top of ‘normal’ scrapping, which is represented using a Weibull reliability function) – this occurs when the fixed and variable operating costs are higher than total costs of a new vehicle.	The purchasing costs of new technologies and new car components change through time according to learning curves that depend on cumulative sales and on technology support policy. Non-monetary adoption costs, imitation and social learning effects are also represented in the model	2030

In the models summarized in Table 3, annual sales are obtained directly either using econometric techniques or calibrated functions. All models reviewed in this category are unimodal estimates of car demand. In this class of models, the vehicle stock is modelled as the sum of all surviving cars from previous vintages and the new sales[31].

In the ALTER-MOTIVE model, econometric estimates are performed at the aggregate level for each vehicle category. In the TAFV model, both the buy decisions at the household level, and the composition of the sales are modelled with a nested logit function whose parameters have been determined using "first economic principles" (see Section 3.4). Kloess and Müller (2011) use a calibrated demand function at the aggregate level, and the market shares of technologies are estimated with a MNL calibrated on their specific service costs.

The most important advantages and shortcomings of this approach are similar to those of estimating the demand for the total car stock. Moreover, this approach does not take into account that cars are durable goods, and thus the demand for *new* cars is not independent from the composition and the usage patterns of the existing stock: for a given GDP, for instance, the demand for new cars will be higher of the annual mileage of existing vehicle increases. This is an important additional reason why this approach should be considered as a solution-of-the-last-resort if other approaches are not feasible, e.g. due to the unavailability of data.

Finally, Table 4 discusses models that use other approaches to modelling annual sales. These are models that rely heavily on expert judgement in their projections.

The key advantage of this approach is that, compared to the alternatives, it requires less data and less modelling effort. The most important drawback is that the mechanism underlying the projections is not transparent at all: if two different experts end up with two completely different projections, it is very difficult to understand the drivers behind these differences. With explicit economic models, tinkering with key parameters leads to a better understanding of the forces driving the results. However, given the level of uncertainty when it comes to long term projections, one may argue that economic models also rely on assumptions whose implications are difficult to understand, and that the higher transparency of economic models is mainly an illusion which does not warrant the cost of developing these models.

One final point is that it is possible to combine several approaches. For instance, Fulton et al. (2017b) rely on the MoMo projections for total vehicle stock, but use a logit model to split sales according to model type.

[31] With one exception: in the description of the TAFV model, there is no explicit discussion of the vehicle stock.

Table 3 Models with direct estimates of total annual vehicle sales

Model	Travel demand	Scrappage	Treatment of AFV	Time Horizon
TAFV family	No	Not in TAFV. From MA3T on, historical scrappage rates	Utility function based on economic principles and consensus estimates. From MA3T on, inclusion of transition dynamics and user heterogeneity.	No explicit time horizon in TAFV. MA3T and LAVE-Trans has been used for projections up to 2050.
ALTER-MOTIVE	Vkm are estimated per vehicle category	Not discussed	The share of biofuels has been introduced exogenously, but it is not clear how the introduction of other types of alternative fuels has been modelled Investment costs for new technologies decline exponentially with time.	2030
Kloess and Müller 2011	Distance travelled is represented as function of fuel prices and GDP.	Survival follows a Weibull distribution	The barriers to the diffusion of the AFVs are summarized in an index that enters the utility function	2050

Table 4 Other approaches to changes in vehicle stock

Model	Travel demand	Modal split	Vehicle stock (quantity)	Vehicles sales (quantity)	Vehicle sales or stock (composition)	Scrappage	Treatment of AFV	Time Horizon
MoMo	Follows exogenous changes in GDP, population, and fuel prices	Projections based on trends combined with expert judgement	Gompertz curves as a function of per-capita GDP	Not specified	Projections based on trends combined with expert judgement	Not specified	Expert judgement	2095
Roadmap	Follows exogenous changes in GDP, population, and fuel prices	Projections based on trends combined with expert judgement	Function of total travel, modal shares, and annual VKT per vehicle	Not specified	Projections based on trends combined with expert judgement	Not specified	Expert judgement	2095
Imaclim-R	Explicit utility function containing composite indicator of travel activity above minimum level determined by spatial structure and infrastructure. Utility is maximised under budget constraints and fixed time budget form mobility.	Four transport modes included in the user's utility function.	Motorization rate is related to per capita disposable income, with an income elasticity that varies depending on the rate of motorization	Sales are the difference between the motorization rate and the remaining stock of previous vintages.	Choices among transport technologies are based on logit function.		Takes into account positive network externalities and path dependencies. The market share of each new vehicle technology is obtained by a logit function which represents heterogeneities in household choices and the coexistence of several different vehicle types. Exogenous maximum on the market share of EV. Capital costs decrease endogenously in function of the learning-by doing process.	2100

5. Potential for improvement and conclusion

In this final section, we summarize the key findings of our literature review, and propose an approach to car stock modelling that depends on the time perspective taken in the projections on the one hand, and on data availability on the other hand.

5.1. Summary of key findings

In this paper, we have reviewed the state-of-the-art of vehicle stock modelling in long-term projections of transport demand. The key objective was to understand the potential and drawbacks of different approaches to represent new trends in mobility (such as the expected breakthrough of shared automated electric vehicles) in the PLANET model. These new trends are likely to affect several dimensions of transport demand, such as the annual mileage per car, the number of cars, the length of commuting and the attractiveness of public transport.

In Section 2, we have discussed key criteria used to classify transport models:

- The integration of the transport model in a model of the wider economy;
- The relation between overall travel demand and vehicle choice;
- The treatment of indirect emissions;
- The opportunity cost of time spent travelling;
- The relative weight given to explicit economic modelling versus expert judgement in modelling future mobility choices.

The choices made in these areas generally affect the vehicle stock model in some way or another.

The PLANET model can be described a sectoral model of the transport sector, which follows the "service demand approach": it first models travel demand for all modes combined, and then allocates total demand to individual modes according to a nested CES function. It considers only well-to-wheel emissions: it does not consider the environmental effects of the production and the scrapping of vehicles, nor the damages linked to the building of the transport infrastructure. The emissions of biofuels do not account for ILUC effects. The opportunity cost of time is a term in the generalised cost of transport, and no exogenous constraints are imposed on total travel time. Therefore, PLANET is well equipped to represent the reduced opportunity cost of travel time with automated cars. Some aspects of the model have firm groundings in micro-economic theory (such as the modal choice), while others are based on simple extrapolations of existing trends.

In Section 3, we have moved on to a general discussion of vehicle stock modelling.

In the PLANET model, the total number of cars is determined at the aggregate level: it is the number of cars that is needed to meet the expected mobility demand, as expressed in the number of vehicle km calculated in the trip distribution model. However, the split of aggregate demand over individual vehicle classes and the expected mileage are determined in a calibrated Indirect Utility Car Ownership and

Use Models. No attempt is made to estimate the number of cars per household. In short, PLANET is an aggregate model of the car stock composition.

Car stock models are all situated on a continuum between "pure" top-down and "pure" bottom-up modelling of transport technologies. PLANET is a "hybrid" model: although the modal and time choice are represented with a nested CES function, it is only for passenger cars that the demand is explicitly modelled in detail, up to the level of the market segments used in the COPERT methodology. For long-term projections, there is also a strong need to explicitly represent processes of technological change in the vehicle stock, which is currently missing.

We have also briefly explored some of the approaches that have been used to relax the restrictive behavioural assumptions underlying most 'traditional' vehicle stock models. In PLANET, the aggregate demand for cars is split in the demand for broad categories of "car types" according to a calibrated nested logit function, which does not account for individual household characteristics. Linking vehicle registration data with household surveys holds some potential to improve the representation of consumer behaviour in PLANET.

Finally, we have discussed approaches to model the demand for vehicle types that have currently low or zero market shares, but that are expected to have an important potential in the long run. The most promising approaches consist in the use of combined RP and SP data (if these are available), or in the use of "synthetic utility functions", whose parameters are based on "first principles" or extensive literature surveys.

In Section 4, we have focused specifically on the problem of vehicle stock modelling in long term projections. Of all the approaches that we have discussed, the one with the most solid foundations in economic theory consists in taking the annual sales of vehicles as the "residual" variable. In this approach:

– The existing stock of vehicles is retired according to a scrappage function.
– The total vehicle stock is estimated. One common approach is to calculate the stock that is *needed* to meet travel demand (expressed in pkm). This calculation requires the following steps: (a) translate travel demand expressed in pkm in travel demand expressed in vkm (b) divide total vkm demand by the annual distance travelled per cars in the existing stock. This step thus requires values for the load factors and the average vkm for existing vehicles.
– The annual vehicles sales are calculated as the desired car stock minus the actual car stock inherited from previous vintages.
– Total sales are split in classes (e.g. according to fuel or vehicle size) using a discrete choice function.

In order to represent the impact of shared mobility, it is important that parameters such as the load factors and the annual mileage of cars can be modified according to the scenario that is under consideration.

Given the level of uncertainty when it comes to projections for the very long term, one may argue that economic models mostly rely on assumptions whose implications are difficult to understand, and that models that rely mainly on simple assumptions based on expert judgements can be valid alternatives.

5.2. Proposal for a differentiated approach

The priorities for improving projections of vehicle ownership and stocks depends to a large extent on the time perspective taken, and on the availability of data. We summarize here some elements that have been identified in the literature (Pietzcker et al. 2014, Pietzcker et al. 2014, Wilson et al. 2014, Mercure et al. 2017, Yeh et al. 2016, Morton et al. 2011, Sims et al. 2014, Polzin, et al. 2014, Lyons and Davidson 2016, Mishra et al. 2013).

Let us first consider the **short run**. At an abstract level, we can define "short term" as a time period during which preferences remain stable and during which new technologies do not fundamentally affect the composition of the existing stock (as opposed to the composition of the sales). For practical purposes, this could correspond to projections for up to 5 years in the future. In this time perspective, it can be assumed that the preferences for new technologies can be understood from observed behaviour. For the purpose of evaluating transport policies whose impact is likely to be felt in the short run[32], one can continue to use RP studies, keeping in mind the following elements:

– Models predicting car ownership at the household level should reflect that some elements that are crucial in the choice of a first car by a household (such as range), may be less crucial for a second one.

– The choice behaviour of fleet managers is likely to be different from the choice behaviour of private households, which is especially relevant in the case of company cars.

– The choice set should include all relevant technologies.

– As leisure trips are becoming increasingly important, models should reflect that the value of time varies according to the trip purpose. In the case of public transport, the value of time should also reflect the quality of the service and congestion levels.

As discussed in Section 3.4, there is a strong case for combining RP with SP surveys. In the absence of robust RP or SP data for the country or region under consideration, one can use the "synthetic utility function" approach instead.

In the current version of the car stock model in PLANET, the nested logit model has used values from the literature to estimate the elasticities with respect to monetary fixed and variable costs, and with respect to (aggregate) demand. The ASC have been used to calibrate the model, so that simulated and observed market shares of all vehicle classes are equal. One limitation of the current approach is that the shares of AFV are exogenous.

It can be envisaged to estimate a RP model with the data of Vehicle Registration Service (DIV). The key advantage of this approach is that it gives access to detailed and comprehensive vehicle data. However, it does not contain socio-economic data of the households that own the vehicle. The registry could be linked with sample data from national (BELDAM[33]) or regional (OVG[34]) travel surveys, to link car features with socio-demographic data. One risk of using survey data could be that it would leave out some

32 For instance, a tax shift from the fixed taxation of cars to congestion pricing.
33 http://www.beldam.be/, in Dutch and French only.
34 http://www.mobielvlaanderen.be/ovg/, in Dutch only.

vehicle types with very low market shares. It is also possible to combine the DIV data with CAR-PASS[35] data on annual mileage. These issues will be explored in future work.

To the best of our knowledge, no SP surveys are currently available that could be combined with these RP data.

Another possibility would be to replace the existing calibrated model with a synthetic utility function model – this would allow an endogenization of the market shares of AFV.

Next, let us consider the **medium term**, which we can define as a period in which there are observable changes in collective behaviour and in the average characteristics of vehicle stocks as a result of new social norms and technologies. For practical purposes, this could correspond to projections for up to 10-15 years in the future.

Compared to models that are used for short term projections, models that target the medium run should reflect that:

- People are more flexible in the medium run than in the short run. For instance, changes in location choice leave more room for changing the length of the daily commute, the modal choice, vehicle technology choice, load factors (for instance, through a greater uptake of shared modes) … From a modelling perspective, this reinforces the need to understand how people's transport behaviour relates to "fundamentals" such as their lifestyles and value systems, but also how features of the areas of residence and destination (urban, suburban, rural) affect mobility behaviour.
- An important driver of increased mobility in developed countries is the mobility of elder people who are more affluent and healthier than previous generations. Moreover, compared to previous generations, they tend to have more car dependent lifestyles. As societies age further, this will lead to further increases in travel (and especially car travel) for leisure purposes, which is much more variable than travel for commuting purposes.
- In the medium run, the possibility also arises that social norms change. This requires the explicit representation of neighbourhood effects, the transmission of information, fads, fashions and bandwagon effects[36], including intra-household dynamics.
- The demand for transport and the structure of the supply side are increasingly affected by technological developments outside the transport sector. For instance, the size and the direction of logistical flows may be profoundly affected by 3-D printing[37]. In passenger transport, the future evolution of

[35] Car-Pass is a Belgian non-profit organization charged by law to combat odometer fraud.

[36] "The bandwagon effect is a phenomenon whereby the rate of uptake of beliefs, ideas, fads and trends increases the more that they have already been adopted by others" - https://en.wikipedia.org/wiki/Bandwagon_effect. As noted by Mercure et al. (2017), with social influences in vehicles choice, the diffusion of new technologies may become path dependent. On the other hand, Morton et al. (2011) argue that EV adoption is likely to involve more rational evaluations, given the financial and personal impact of adopting a completely new technology for the first time.

[37] In product categories where there is scope for customisation (for instance, accessories such as smartphone cases) companies can use 3D printing to sell their products directly to consumers. Thus, there are no logistical costs (transport or inventory of finished goods) until the demand has materialised (Rayna and Striukova, 2016). An even more fundamental change is that current global supply chains tend to be characterised by (a) mass production far away from the customer, taking advantage of low labour costs and economies of scale in production (b) mass transport of finished or semi-finished goods over long

the relative preference for physical versus virtual accessibility will also be key in the evolution of trip generation.

– A key element in the uptake of AFV is the existence of network effects in the refuelling infrastructure. Initially, these network effects can be a major barrier to adoption. However, they can also lead to self-reinforcing dynamics once a certain threshold in ownership and infrastructure density has been reached. Another network effect is the complementarity between electric, shared and automated mobility. These network effects, and the resulting path dependency, need to be represented in models.

– The combined impact of higher consumer flexibility, of possibly major changes in social norms and of network effects imply that the medium run is significantly more uncertain than the short run.

One possible approach to medium term projections, would be to start from existing discrete choice models[38] , enriched with models of social learning (on the demand side) and learning-by-doing (on the supply side). In order to represent the uncertainty regarding future developments, one can perform simulations with random future changes in the WTP and prices to assess the robustness of projections – for an application to the adoption of automated vehicles, see Bansal and Kockelman (2017).

In the **long run**, all the difficulties encountered in medium term projections become fundamental. Future patterns of car ownership and use may change fundamentally, society may reach a saturation point in vehicle ownership[39] (which is distinct from a saturation point in distance travelled[40]), elasticities may vary (maybe endogenously), technologies may appear that we can currently not even envisage...

As discussed by Lyons and Davidson (2016), there "is uncertainty concerning what people in future will want to do and what technology in future will enable us to do". They view this problem as a problem of deep uncertainty, where the collection of additional data will not reduce the level of uncertainty. They conclude that, in this context, scenario planning can help "demonstrate how divergent, plausible futures can emerge; avoid 'group think' and foster 'contrarian thinking'; and challenge conventional wisdom".

This route could be the most appropriate for long term projections: transport modellers should acknowledge the fundamental uncertainties in the future development of preferences and technologies, and consider extreme scenarios only in order to enlighten policy makers about the possible routes that the future can take, rather than provide them with a central estimate that would be based on a simple extrapolation of current trends.

distances, using containerised transport. 3D printing can move the production phase closer to the final customer, and the share of bulk in long distance transport will increase compared to the share of containerised transport (Florea Ionescu, 2015). The magnitude of these changes is still subject to considerable uncertainty.

38 As discussed above this could refer to RP studies, preferably complemented with SP studies, or alternatively, from synthetic utility function based on 'first principles'.

39 In several models we have discussed, the possibility of a saturation point is explicitly represented (POLES, IPTS, UKTCM, Hennesy and Tol).

40 Another related, but distinct, concept is the saturation of the transport system when travel demand increases for a given infrastructure. Transport models that use the generalised cost of transport as one of the determinants of transport demand usually endogenize the impact of congestion on total transport volumes, modal shares and (in the case of 4-step models) route choice.

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7. Annexes

7.1. The GCAM family of models

a. GCAM

The Global Change Assessment Model (GCAM) has initially been developed by the Pacific Northwest National Laboratory (PNNL) in the US. It is a global (14 regions, multi-sector) partial equilibrium, technologically detailed IAM that links representations of the energy system[41], the agriculture and land use system, and the climate system. GCAM runs in 15-years time steps from 2005 through 2095, and calculates equilibria in each time period. The current transportation module has been developed in collaboration between PNNL and the Institute of Transportation Studies (ITS), University of California, Davis (Kyle and Kim 2011, Girod et al. 2013b, Yeh et al. 2016).

The most recent documentation of the transportation module that we are aware of, is Mishra et al. (2013). Unless stated explicitly otherwise, everything in this section follows this source. Other discussions of GCAM include: Daly et al. (2014) and Pietzcker et al. (2014).

In GCAM, the transportation sector is broadly divided into passenger and freight, with a further distinction between short- and medium-distance transport on the one hand, and long-distance transport on the other hand (international shipping and aviation for freight, aviation for passenger transport). In the most recent publicly available version of the model, the choice variables for consumers include modal choice (including non-motorized modes and electric bikes), vehicle technologies (e.g. internal combustion engine vehicles versus electric vehicle) and size classes.

Expressed in passenger kilometres, the fundamental equation for total passenger transport (*Dp*) in region r and *future* time period t is:

$$D_P^{r,t} = \sigma^r \left(Y_I^{r,t}\right)^{\alpha} \left(P_I^{r,t}\right)^{\beta} \left(N_I^{r,t}\right).$$

Where σ is a base year (2005) calibration parameter. Y_I is the index for income in the form of per-capita GDP (defined on a purchasing power parity basis) at time “t” divided by per-capita GDP in the base year (2005). P_I is the index of price of transportation (or generalized user cost) aggregated across all modes, size classes, and technologies and calculated as the ratio of price in time “t” to the price in base year. N_I is the population in region r, in time t. Finally, α and β are income and price elasticities, respectively, with respect to per capita passenger demand.

The equation for freight transportation demand (D_F) in region r and future time period t is similar.

GDP, population and the elasticities are exogenous. As the fuel prices are endogenous to GCAM, the aggregate price of transportation services is also endogenous. The total generalized cost of transportation services (P, in \$/pkm or \$/tkm) is the weighted average cost of each available mode:

[41] Covering primary energy production, transformation, and delivery (Kyle and Kim 2011).

$$P^{r,t} = \sum_i (S^i)\,(P^{i,r,t})$$

where S^i is the share of mode (i) in terms of pkm or tkm. As the share of each mode depends on its cost (see further), changes in the cost of an individual mode has both direct and indirect effects on the total cost of transport.

The costs by mode are in turn calculated as the weighted average costs of all constituent size classes of the vehicles, plus the time value costs (value of travel time; VTT). The time value cost is assumed to be the same for all size classes and propulsion technologies within a given mode:

$$P^{i,r,t} = P^{i,r,t}_{time} + \sum_i (S^s)\,(P^{s,i,r,t})$$

where S^s is the share of size class (*s*) under mode (*i*) in terms of pkm or tkm.

The value of time depends on: the wage rate *W* ($/hour); the average door-to-door speed[42] of mode *i*, S_p (km/hour), which varies by mode, region and time; and a unitless parameter δ representing the cost associated with travel expressed as a multiplier of the wage rate (value of time, or VOT).

$$P^{i,r,t}_{time} = \delta^i \frac{W^{r,t}}{Sp^{i,r,t}}$$

It is assumed that passengers dislike travel and thus that the VOT multiplier is positive[43]. The wage rate is calculated as the per-capita GDP[44] divided by the number of working hours in the year (Kyle and Kim 2011). This formulation implies that economic growth will promote a modal shift towards high-speed modes, which will be partly counteracted by the increased cost of service provision.

The costs for each size class (s), in turn, are calculated as the weighted average costs of all constituent technologies (j). These technology costs can be broken down in fuel costs and non-fuel costs:

$$p^{j,s,i,r,t} = \frac{(P^{r,t}_{fuel})(EI^{j,s,i,r,t}) + p^{j,s,i,r,t}_{NF}}{LF^{i,r,t}}$$

Where, P_{fuel} is the fuel price ($/MJ), EI is the vehicle energy or fuel intensity (MJ/vkt), P_{NF} is the non-fuel price of transportation for the given mode, and LF is the exogenous load factor defined either as passengers per vehicle or tonnes per vehicle. In this equation, only the fuel prices are endogenous. However, the exogenous variables can vary according to technology and time period.

For private modes like cars and two-wheelers, the non-fuel price (P_{NF}) of transportation is estimated using a bottom-up approach, starting from estimates of the purchase cost of vehicles (including taxes and registration fees) as well as variable and fixed annual operating costs. For public modes like trucks,

42 The specific numbers used come from a literature search, with values generally similar to Shafer's research. The bus waiting time is taken into account. E-mail from Page Kyle on 20 May 2017.

43 This multiplier takes into account wait costs for public transport modes and air travel, and may thus need to be revised if investments in public transport and airport capacity reduce the wait time – see Mishra et al. (2013).

44 The GDP figures used by GCAM do not allow to separate capital income. E-mail from Page Kyle on 20 May 2017.

buses, air, rail, and ships, a top-down method was used whereby the sum of fares and government subsidies are assumed to capture all economic costs.

In order to model the vehicle stock, it is assumed that the 2010 stock follows a (mostly) linear retirement function, as it is considered to consist of a blend of different vehicle ages, and then starting in 2015, each cohort is modeled with an s-shaped survival curve whose parameters are tuned to values presented in the US Transportation Energy Data Book[45].

The market shares of the technologies, the size classes and the transport modes are determined per region and time period, according to the following *calibrated* logit formulation:

$$S^{i,r,t} = \frac{(SW^{i,r})(P^{i,r,t})^{\lambda_i}}{\sum_i (SW^{i,r})(P^{i,r,t})^{\lambda_i}}$$

where S is the market share, SW is the share weight, Pi is the cost of transport service, and λ is the logit exponent. The share weight is a calibration parameter, which was obtained by iteratively running the model and choosing values that were capable of replicating the trends seen historically in OECD nations[46].

In GCAM, the travel speeds per mode are exogenous. In other words, the cost of congestion is not endogenous in the model.

The roads sector in GCAM distinguishes the following motorized modes: car and light truck (or simply cars), two-wheeler, three-wheeler, bus, and freight truck. Energy consumption in the base year is calibrated to the International Energy Agency (IEA)'s World Energy Statistics (IEA 2007).

The model considers the following alternative technologies for each car subsegment: CNG, HEV, BEV and FCEV. The alternative cars are assumed to have similar curb (kerb) weight (CW), "equivalent" engine/motor power load factors and VKT as the reference ICE vehicle. It should be noted that the assumptions about various alternative technologies in Western Europe are based on TREMOVE.

The current version of the model largely ignores R&D and infrastructure costs (such as road infrastructure, fuelling stations and charging infrastructure). However, GCAM does take into account the constraints due to infrastructure availability by exogenously reducing the market shares of alternative-fuel vehicles (McCollum et al. 2016b and Wilson et al. 2014).

The changes in the vehicle stock are calculated as follows: (a) the model assumes constant mileage per vehicle per year (b) the new vehicle stock is the stock that is required to meet the annual mileage per year, taking into account the mileage performed by the historical vehicle stock left after scrappage[47].

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45 Personal e-mail from Page Kyle (PNNL) dated 12 May 2017

46 Personal e-mail from Page Kyle (PNNL) dated 12 May 2017. Following a recent number of model inter-comparisons, the authors haven't yet seen any need to modify the assumed logit exponents.

47 E-mail from Page Kyle on 20 May 2017.

b. POLES

This section follows the summary in Girod et al. (2013b)

The POLES model is a dynamic equilibrium model of the World energy sector that provides comprehensive energy balances and associated GHG emissions (Kitous et al., 2010). The transport sector module describes various transport modes for passengers (pkm) and freight (tkm): road vehicles (light and heavy for goods, cars, motorcycles and bus for passengers), rail, and air, fluvial. It does not include non-motorized modes[48]. The key drivers of the mobility needs are income and energy prices.

To describe transport demand, POLES use an approach similar to the one used in the GCAM model. However, in POLES, this equation is used to represent the demand for the single modes and thus indirectly also the mode split. In other words, the model does not represent directly substitution effects between modes. However, as the demand for modes reacts to energy prices, there is an indirect link.

Future mobility is capped by exogenous regional saturation levels (e.g. maximum level of car per capita). Load factors are exogenous.

For new road vehicles, a MNL *simulation* allocates the market shares of vehicle types and fuels as a function of life cycle costs and the availability of infrastructure such as refuelling stations.

POLES connects the fuel prices in transport to the wider energy system; the prices include production cost, distribution costs and local taxation policy.

c. TIMER

All the information in this section is based on Girod et al. (2013b).

The TIMER model is part of the IMAGE IAM (Integrated Model to Assess the Global Environment). The TRAVEL model in TIMER covers both passenger and freight transport. It includes 7 travel modes, including non-motorized ones.

Modal choice for passenger is affected by the exogenous travel time budget (TTB) and travel money budget (TMB) relationships[49] (which can however vary over time), while modal choice in freight transport is somewhat simpler.

As the transportation model is connected to the wider energy system, energy prices are endogenous.

Total service demand is projected using an approach similar to GCAM. However, money and time budget are used as exogenous input to adjust total travel demand and mode split. For freight transport, industrial value added is used as driver rather than GDP (which is one of the distinguishing assumptions of TIMER).

The market shares of different modes, vehicles, or fuels are allocated with the same type of logit formulation as used in GCAM, with consideration of time use costs.

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[48] Presumably because they have no direct impact on energy demand.

[49] See for instance Schafer et al., 2010.

7.2. The TAFV family of models and applications

a. MA3T

The Market Acceptance of Advanced Automotive Technologies (MA3T) is a NMNL model developed in the US[50] who can easily be adapted to other countries (Wilson et al. 2014). Unless stated otherwise, this section is entirely based on Liu and Lin (2017).

MA3T has been developed by Oak Ridge National Laboratory (ORNL) for the U.S. Department of Energy, and is a further development of the TAFV (Transition toward Alternative Fuel Vehicles) model discussed in Section 27. A similar model is LAVE-Trans, which is discussed in the next Section.

Compared to E4 models, the scope of MA3T is narrower, as it only considers the personal vehicle market (Bunch et al. 2015).

Compared to TAFV, the most important innovation in MA3T are (a) the incorporation of transition dynamics, such as manufacturers' learning by doing and economies of scale as vehicle sales increase (b) user heterogeneity. Just as TAFV, it is a NMLM, with the "buy" decision at the top of the structure. Consumers can choose between passenger cars and light-duty trucks, each with a wide range of power-train technologies. The attributes of the choice model are similar to those included in TAFV, but also include technology risk and policies (such as purchase subsidies, tax credits, HOV access, free parking, etc.).

As in TAFV, the ASCs of the NMNL are calibrated to most recently available vehicle sales data. In addition, MA3T "includes feedback loops, where non-technology factors influence next year sales which in turn change non-technology factors one year after". The model assumes that, with time, the unobserved attributes of Plug-in electric vehicles (PEVs) will become similar to those of conventional ones, and thus that the ASCs will converge as well.

MA3T divides US light-duty vehicle consumers into 1,458 segments according to the following dimensions: 9 census divisions, residential areas (urban, suburban and rural), attitudes toward novel technologies (early adopters, early majority, and late majority)[51], three levels of intensity of vehicle usage, and the availability of charging facilities. For each segment, there is a "representative consumer". For instance, "the disutility costs of an electric vehicle are estimated by MA3T to be higher for a rural dweller who drives frequently and is typically a late adopter of new technologies than they are for an urban dweller who drives relatively little and is an early adopter" (Wilson et al. 2014)

Liu and Lin (2017) admit that, in the medium to long run, these segmentations are subject to substantial uncertainty.

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[50] http://cta.ornl.gov/ma3t/

[51] While early adopters are willing to pay (WTP) for innovativeness of advanced technologies early and late majority are averse to their risk.

The dynamics of the model are captured through the following relations:

– The vehicle *stock* at year t affects (a) vehicle price at year t+1 through the manufacturer learning by doing, and (b) consumers' risk preference for the technology at year t+1;
– The vehicle *sales* at year t affects make/model diversity of the technology at year t+1.

In the absence of hard data to estimate learning rates or progress ratios, Liu and Lin (2017) propose educated guesses for the central values, with considerable variation around these central values for sensitivity analysis. Other key sources of future uncertainty are: (1) the sensitivity of car buyers' choices to price, (2) PEV make and model diversity (which will be smaller than the diversity on offer from similar conventional vehicles – see McFadden 1978), (3) the value of time, (4) the perceived cost of range assurance for BEVs, and (5) how the market will value the risk and innovativeness of advanced technologies (6) the users' willingness to pay for fuel economy (7) the future evolution of charging facilities (the location and charging speed of home, public and work recharging situations).

To simulate the evolution of the vehicle stocks by technology and by vehicle age, the user can for instance use the vehicle scrappage component of MA3T. The vehicle scrappage in MA3T is based on the historical data in the US Transportation Energy Data Book, and is left exogenous.[52]

b. LAVE-Trans

The Light-duty Alternative Vehicles and Energy Transitions (LAVE-Trans) model has been developed for the project "Analyzing the Transition to Electric Drive in California" for the International Council on Clean Transportation, and has also been used by the US National Research Council's study, Transitions to Alternative Vehicles and Fuels (NRC, 2013, Appendix H[53]). It "represents consumers' choices among vehicle technologies, the effects of scale, learning and technological change on the costs and performance of vehicles, and the supply of energy for vehicles" (Greene et al. 2013).

Consumer behaviour is modelled with a NML model and key choice model parameters have been derived from basic assumptions – this follows the approach already adopted for the TAFV model (Greene 2001) discussed above. Scrappage rates are based on historical data.

LAVE-Trans includes feedback loops to represent the external benefits generated by the adoption of new technologies: reduction in the risk aversion of the "majority" consumers, increases in the supply of refuelling infrastructure when more alternative fuel vehicles are sold, learning-by-doing and economies of scale. Reductions in risk aversion and increases in the supply of refuelling infrastructure make the new technologies more attractive, leading to new sales, etc. The feedback loops operate with a one-year lag. The general approach of the model is thus really close to MA3T (Greene et al. 2013).

The model also calculates energy use and well-to-wheel emissions.

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52 E-mail correspondence with Zhenhong Lin on 18 April 2017.
53 Model documentation can be found on line at http://www.nap.edu/openbook.php?record_id=18264&page=331

7.3. The IPTS transport technologies model

The IPTS transport technologies model was originally planned as an extension of the POLES energy market model, but it may be used as a standalone model as well. It is extensively discussed in Christidis et al. (2003), of which this section is a summary.

The model simulates the way that consumer choices concerning passenger cars are influenced by exogenous variables such as changes in car and fuel prices, technological developments and general socio-economic trends (GDP and population growth) [54].

Car ownership levels are modelled with a country-specific *modified* Gompertz function. To be more concrete, it is assumed that the Gompertz function describes the *long run* relationship between vehicle ownership and per capita income, but that there are lags in the adjustment of vehicle ownership to per capita income. These lags can result from the necessary build-up of savings to afford ownership, the gradual changes in housing patterns, etc. This is represented with the following partial adjustment mechanism:

$$C_t = C_{t-1} + \theta \cdot (C_t^* - C_{t-1})$$

where θ is the speed of the adjustment ($0<\theta<1$).

Substituting C_t^* in the last equation, the result is the equation used in the model:

$$C_t = \gamma \cdot \theta \cdot e^{\alpha \cdot e^{\beta \cdot G_t}} + (1-\theta) \cdot C_{t-1}$$

where γ is the saturation level, θ is the speed adjustment factor of the curve, α and β are negative parameters defining the shape of the Gompertz function and G_t is the GDP per capita expressed in PPP.

Note that the Gompertz is used to represent all car categories – the distribution of overall ownership across customer categories and technology types is described below.

New registrations are a result of either the change in the overall car ownership level, or of the replacement of cars that are scrapped or removed from the car park (i.e. in the case of used car exports).

The number of new cars registered per country (or the car sales) is a function of the variation of the number of cars per capita, the population and the total amount of scrapped vehicles:

$$NCR_t = (C_t - C_{t-1}) \cdot POP_t + TOTSCR_t$$

where:

- NCR_t is the number of new car registrations at time t
- C_t the per capita car ownership
- $TOTSCR_t$ the number of cars removed from the car park during the period

[54] Future prices and GDP are imported from the POLES model.

The **number of the cars removed** each year from the park is modelled through country and technology specific survival rate curves for each cohort of cars.

In the absence of sufficient data with respect to car scrapping, the dynamics of the car park were modelled on the basis of the historical data on new car registrations and car park figures. The dynamics of fleet ageing are described by the following equations:

$$\begin{cases} CARFLEET_t = \sum_{car} \sum_{i=0}^{\infty} SURPC_{car,i} \\ SURPC_{car,i} = NCR_{t-i} \cdot SR_i \\ SR_i = 1 - e^{(a \cdot e^{-b \cdot i})} \end{cases}$$

Where:

- $CARFLEET_t$ the number of cars in circulation at time t
- $SURPC_{car,i}$ the number of cars that belongs to category car and are i years old at time t.
- i the age of the cohort
- SR_i the survival rate of the cohort i years old, which is computed also following a Gompertz survival model, based on historical data.

The survival curve rate can itself change over time, because of technological progress and changing incomes. The model allows the incorporation of the technological progress in the determination of parameters a and b.

An important point raised in the model documentation is that the structure of the second-hand market only matters for the environmental impacts of car use in the case that this market has an important international trade component.

The model distinguishes between 3 types of users for each country, each corresponding to different preferences.

The model currently includes 7 technological options, covering both conventional or emerging technologies. For emerging technologies, projections by industry experts were used. In the sense, the model is conceived more as a scenario analysis tool than as a prediction tool.

The model allocates new car registrations per technology for each user group. The utility for each category of use or customer is expressed as follows:

$$U_{cust,t} = U_{cust,t-1} \cdot e^{\left(\alpha_{cust} \cdot \left(\frac{G_t - G_{t-1}}{G_t}\right) + \beta_{cust} \cdot \left(\frac{P_t - P_{t-1}}{P_t}\right) + \gamma_{cust} \cdot \left(\frac{C_{t-1} - C_{t-2}}{C_{t-2}}\right)\right)}$$

where:

- α_{cust} is the adjustment parameter for the income per capita.
- G_t is the GDP per capita.
- β_{cust} is the adjustment parameter for urban population

- P_t is the percentage of urban population.
- γ_{cust} is the adjustment parameter for the number of cars per capita
- and C_t is the number of cars per 1000 inhabitants.

These utilities are used to compute the share of each customer in the *total* number of *new* car registrations per country:

$$CUSTSH_{cust,t} = \frac{U_{cust,t}}{\sum_{cust} U_{cust,t}}$$

The decision to select a particular car technology depends on the utilization costs associated with this car category. The share of each car category per customer is computed in two stages. Initially, it is assumed that there are no capacity constraints, and each market segment is allocated its "a-priori" share following a Weibull distribution with the adjusted user cost for each technology as input:

$$DEMSH_{car,cust} = \frac{ADCOST^{b}_{car,cust}}{\sum_{car} ADCOST^{b}_{car,cust}}$$

where:

- $DEMSH_{car,cust}$ is the share of registrations of car category car for each user group cust (demand share without capacity restrictions).
- $ADCOST_{car,cust}$ is the adjusted (by the user preference) cost of car category *car* for user *cust* – for instance, for users in urban areas, the use of large vehicles can be inconvenient, and then the 'objective' financial costs can be 'scaled' up'.
- b is the parameter of the Weibull distribution.

This "a-priori" share can be viewed as a kind of absolute measure of the "attractiveness" of a given car (or technology) category within each customer category.

The second step of the calculation involves the application of the so-called Wood algorithm that allocates demand by priority to the technologies. This is needed because, for a given technology, it is possible the modelled demand exceeds the supply capacities. We refer to the full documentation for more details on this allocation mechanism.

7.4. IEA MoMo and ROADMAP

The Mobility Model (MoMo) of the IEA (Fulton et al., 2009) and the Roadmap model by the International Council on Clean Transportation (ICCT) are very similar in approach and will therefore be discussed together. All information in this section is based on Girod et al. (2013b) and Yeh et al. (2016).

MoMo and Roadmap both cover the global transportation sector.

They are **stand-alone models**, in the sense that they are not fully integrated with the wider energy system. However, MoMo uses a manually iterative process to achieve consistency in energy use and GHG emissions with the IEA's annual Energy Technology Perspectives (ETP) scenarios, which follow from a TIMES-based optimization modeling system.

An advantage of the lack of integration with the wider system, is that it allows MoMo to be rich in technical detail: it includes all transport modes and vehicles types, including non-road modes (rail, air and shipping). It includes IEA estimates of fuel economy potentials, alternative fuels (including biofuels, hydrogen, electricity and synthetic fuels), and cost estimates for most major vehicle and fuel technologies.

Total energy use in MoMo is calculated using the ASIF methodology (Schipper et al., 2000). This approach decomposes GHG emissions as the multiplicative effect of activity (pkm or tkm for freight), mode shares, fuel intensity of each mode[55] (energy use per pkm or tkm using fuel or energy source), and carbon content of each fuel used in a particular mode. MoMo also provides pollutant emissions for all modes, GHG emissions (on a vehicle and well-to-wheel basis) and estimates of the demand for materials needed for the production of LDVs.

Roadmap also covers upstream production and transportation CO_2 and non-CO_2 greenhouse gases (CO_2e) emissions. Moreover, it also includes indirect land-use change (ILUC) emissions based on literature reviews.

Modal split and technology choices in MoMo and Roadmap are based on trends combined with expert judgement, rather than on explicit econometric modelling. The technical detail of the model allows detailed bottom-up "what-if" modelling, ranging from changes in technological trends to changes in mode share or expected policies.

One important difference between Roadmap and MoMo is that Roadmap predicts ownership as a function of total travel, modal shares, and annual VKT per vehicle. In MoMo, vehicle and 2-wheeler travel demands are estimated based on private vehicle ownership rates, which is modeled directly with Gompertz curves as a function of per-capita GDP, while air travel activity is projected based on historical trends. In Roadmap, PKT is projected based on exogenous changes in GDP, population, and fuel prices. Freight service demand is based on simple functions of population, GDP, and fuel prices (except MoMo) in both models.

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[55] Note that, in reality, when the mode share change, the load factor (and thus also the fuel intensity) of modes will change.

7.5. UKTCM

a. Version 1 and application

The UK Transport Carbon Model (UKTCM) is a highly disaggregated, bottom-up model of transport energy use and life cycle carbon emissions in the UK. It provides annual projections of transport supply and demand, for all passenger and freight modes of transport, and calculates the corresponding energy use, life cycle emissions and environmental impacts year-by-year up to 2050. Unless stated explicitly otherwise, the remainder of this section follows Brand (2010).

Some key features of the model are:

– Scenarios describing a range of *possible* external political and socioeconomic developments, which can be identified and characterised through extensive consultation with external experts;

– A high level of technical detail, with more than 600 vehicle technology categories, including a wide range of alternative-fuelled vehicles;

– The potential to model a wide range of policies, including fiscal, regulatory and behavioural change interventions.

One noteworthy element in this approach, is that, in "order that the set of scenarios covers a sufficiently wide range of possibilities, each scenario is relatively extreme – albeit plausible. Descriptions of the most likely developments would be of little help in coping with uncertainty". The model is thus *not* set up as a forecasting model.

The transport system is described at the hand of four linked simulation models:

– the transport demand model (TDM), which calculates the overall level of transport activity and modal shares for passenger and freight movements;

– the vehicle stock model (VSM), which tracks the changes in the vehicle stock at a high level of technical detail;

– the direct energy use and emissions model (DEEM) and;

– the life cycle and environmental impacts model (LCEIM), which also takes into account the impact of the manufacture, maintenance and disposal of vehicles, of infrastructure building and fuel production.

In the TDM, the demand for each of the modes of transport can be either:

– calculated endogenously year by year up to 2050 employing an econometric demand model ("forecasting mode"), for instance as a function of GDP, the number of households, the population's propensity to travel; energy prices, average ownership and operating costs for each vehicle type, etc., or:

– simulated with exogenous assumptions on how travel activity, modal split and trip distances may evolve over time ("simulation mode") – this allows exploring radical changes in consumer preferences and in the transport system.

For each mode[56], the main equation for forecasting overall travel demand T (expressed in passenger-km and tonne-km) in year n, is given by:

$$\frac{T_n}{T_{n-1}} = \left(\frac{GDP_n}{GDP_{n-1}}\right)^{EGDP} \cdot \left(\frac{NHH_n}{NHH_{n-1}}\right)^{ENHH} \cdot \left(\frac{RC_n}{RC_{n-1}}\right)^{ERC}$$

Where:

- GDP = Gross Domestic Product
- NHH = total number of households
- RC = relative vehicle ownership and operating costs (aggregated with pkm or tkm as weights)
- EX = elasticity with respect to X, which can vary over times to represent changing preferences.

The parameters have been estimated at the hand of statistical data for previous years and on transport demand forecasts taken from other studies. Parameters can be disaggregated according to spatial dimensions, such as urban, rural and highway.

The **VSM** breaks down the numbers of vehicles present in the population, by vehicle type, size, technology and age, and allows a detailed disaggregation of the vehicle-kilometres. For all types, the following equation is used for the evolution of the stock over time:

$$NewVehicles(y) = TotalVehicles(y) - TotalVehicles(y-1) + ScrappedVehicles(y-1)$$

The following steps are taken to calculate the vehicle stock:

Key steps in calculating vehicle stock

1. Import of passenger-kilometres and tonne-kilometres from the demand model
2. Conversion of passenger-kilometres or tonne-kilometres produced by the demand model into vehicle-kilometres, based on average load factors
3. Calculation of total vehicle numbers
4. Calculation of total number of vehicles scrapped
5. Calculation of total number of new vehicles needed to meet demand
6. Calculation of vehicle costs for each technology based on technology costs and policy inputs
7. Disaggregation of new vehicles by size
8. Disaggregation of new vehicles by technology (engine type, fuel)
9. Addition of new vehicles to the remaining vehicle stock from the previous year
10. Disaggregation of vehicle-kilometres by technology
11. Calculation of average costs per vehicle type, based on disaggregated vehicle numbers and vehicle kilometres
12. Output of vehicle numbers and vehicle kilometres by technology and travel type to the DEEM and LCEIM
13. Output of relative operating costs (RC) to TDM by vehicle type

[56] See personal e-mail correspondence from Christian Brand (10 May 2015).

Thus, the total number of new vehicles needed are calculated as the residual. In the car market, the models describing the private car market and the fleet market differ slightly, and a different discount rate is applied.

We will limit our description of the procedures used to the procedure of the car market, which is the most complex. For other modes (such as motorcycles, busses, coaches, vans, trucks, aircrafts, trains, ships), we refer to the detailed model documentation. The approach used also depends on the number of cars owned by a household, since buying a first car is considered to be a different type of decision than the purchase of a second, third or business car. We will only elaborate in detail on the decision to own a first car.

A central assumption in the UKTCM is that car ownership grows up to a "saturation point", which is assumed to occur when all those able to drive have their own vehicle. It is modelled on a household basis, with the following key variables:

- household structure (number of adults, number and age of children);
- household disposable income (by year);
- average new car price;
- household location (urban and non-urban), linked to parking and public transport availability, respectively;
- car ownership saturation level (urban and non-urban).

As the average new car price in year n+1 is based on the average car price in year n, weighted by the vehicle-km for each car technology in year n, it is endogenous to the model.

The first step in calculating the share of households owning 1, 2 or 3 cars, consists in estimating a maximum level of the proportion of car ownership. The basic equation to calculate this maximum level for households owning at least one car is given by (where *l* represents the type of the household's location):

$$MaxOwn_{c=1,l,y} = MaxOwn_{c=1,l,0} \cdot f^2$$

Where $f^2 = \frac{D_y}{D_0}$ is the change of the share of the population able to drive relative to the base year. Similar equations apply to households owning at least two cars, while the maximum level for households owning at least three cars remains constant.

The *actual* proportion of households owning at least one car or two cars depends on *MaxOwn*, but *varies* according to the ratio of disposable income for each household (I_y) to the average new car purchase price (R_y) through a sigmoid (S-shaped) curve. The rate of change depends on the car ownership elasticity, e_y. e_y is calibrated to the base year. For each year, the share of households owning at least one or two cars is denoted by y and given by the Equation below.

$$P_{c,l,y} = MaxOwn_{c,l,y} \cdot \frac{(f_y^1)^{e_y}}{(f_y^1)^{e_y} + f_{c,l,0}^5}, \forall c = 1,2; l \in L; y \in Y$$

Where $f_y^1 = \frac{I_y}{R_y}$, and:

$$f^5_{c,l,0} = \left(\frac{MaxOwn_{c,l,0}}{H_{c,l,0}} - 1\right) \cdot (f^1_0)^{e_0}$$

$$e_y = e_0\left(1 + g \cdot \left(\frac{MaxOwn_{c,l,y}}{f^7} - 1\right)\right)$$

Where g and f are calibration parameters.

Similar formulas apply to households with higher levels of ownership.

The scrappage rate of vehicles is also estimated with S-shaped life curves, which vary according to vehicle types. The variables used in UKTCM for modelling vehicle scrappage are:

– average vehicle lifespan;

– financial incentives/disincentives for scrappage;

– changing real price of vehicles.

The following Equation is a modified Weibull distribution, which provides, for the year y, the share of vehicles of a specific type v that remain operating A years after first registration:

$$f^9_{y,a,v,k} = e^{-\left(\frac{A_{v,y}+\delta_v}{\gamma_v}\right)^{\delta_v}}$$

where:

– δ = failure steepness for vehicle type v

– γ = characteristic service life for vehicle type v

The scrappage probability function, θ, is then the ratio of the share of vehicles of a specific age remaining in the current year to the share of vehicles one year younger being present in the population:

$$\theta = 1 - \frac{f^9_{a,v,k}}{f^9_{a-1,v,k}}$$

This probability is multiplied by the number of vehicles present in the previous year to provide the total number of vehicles scrapped. This calculation is performed first for each vehicle type, age and year:

$$S_{a,y,v,z,g} = \theta \cdot V_{a-1,y-1,v,z,g}\,, \forall y \in Y, v \in M, a \in A, z \in Z, g \in G$$

Based on the evolution in the required car stock and the scrappage rate, one obtains the total number of vehicles. In the case of cars, total sales are split according to size and ownership (private and fleet/company) – both parameters stay constant over the time horizon in the default scenario. However, they can be modified by the users.

For each year, a number of alternative vehicle technologies will be available in the market place, and different scenarios within UKTCM can have different pathways of technological development.

In the technology choice module, demand for new vehicles is further split among the different available technologies. The procedure is different, depending on whether the decision makers are private households or commercial organisations.

For private decision makers, a car represents much more than a means of travelling, and personal preferences matter. This would require a behavioural choice model that is based on socio-economic characteristics of the individuals (or households). In the first version of the model, the developers of the UKTCM reckoned that, when alternative fuelled vehicles were part of the choice set, this type of approach was insufficiently developed. The original UKTCM technology choice module has therefore taken a simple approach: it considers annual vehicle costs within a discrete choice modelling framework as well as non-cost factors simulating:

– perceived vehicle performance, which is an aggregate of perceived safety and security, speed, acceleration, range between refuelling, space available and comfort;

– consumer preference: non-cost factors that cannot be explained by cost, performance and market factors, e.g. vehicle colour, style and 'technology loyalty';

– market/infrastructure availability, which includes factors such as availability of and access to fuel as well as market coverage.

For established technologies, the aggregate preference and performance parameter has been estimated with the following equation, which gives the technology choice probability, using historical data:

$$prob_i = \frac{P_i \cdot e^{-c \cdot \frac{EAC_i}{min(EAC_i)}}}{\sum_{j=1}^{m} P_j \cdot e^{-c \cdot \frac{j}{min(EAC_j)}}}$$

With $P_i = perf_i \cdot pres_i \cdot pref_i$

Where:

– P_i: preference and performance parameter for vehicle technology i;

– $EACi$: equivalent annual cost of vehicle technology i;

– c: modelling constant (preset value of c=10 used for model calibrations);

– m: number of vehicle technologies available in modelling year;

– $perf_i$: perceived performance of vehicle technology i;

– $pres_i$: market presence at maturity of vehicle technology i;

– $pref_i$: consumer preference for vehicle technology i.

For each *new and alternative vehicle technology,* the change in P over time is modelled as an S-curve using a logistic function. It is assumed that the new technology improves from a market entry year T_{entry} to a product maturity year $T_{maturity}$, reaching a maximum level P at maturity. P is then estimated, based on the expected future relative market share of the new vehicle technology, compared to some specified conventional comparator, that might be anticipated if the annualised costs of the conventional and new technologies were the same.

For commercial organisations, on the other hand, it is assumed that they will procure vehicles that provide the best return on their investment. In the absence of detailed data concerning the differences in benefits provided by different technologies, it was assumed that the different technologies available for the same vehicle mode and size offer the same level of utility to the organisation. In addition to costs, market availability, infrastructure availability, vehicle performance and technology preference of a commercial organisations have been included via the same non-cost factors described for private cars.

To represent the differences in financial risks involved, the discount rate can be made to vary by vehicle ownership type (private or fleet/company).

The **vehicle-kilometres** computed by vehicle type and journey segment type (e.g. urban car travel) are taken from the TDM and split according to the proportion of vehicle stock of that vehicle type in each technology category, modified to take account of factors such as age and technology. Certain vehicles may be expected to be used for a smaller number of miles than the average, particularly BEV. This feature can be integrated in the model by including a simple weighting factor that reduces the number of vehicle-kilometres assigned to BEV.

The relationship between car age and mileage is taken into account using an age dependent scaling factor. The annual percentage change in mileage as car ages is assumed to be 1% per year for the reference case. The model normalises to the total vehicle-km before final outputs are written to the database.

The distribution of car vkm by technology and age is given by:

$$VKM_{y,t,v=2,s,a} = \left(1 + \varepsilon \cdot \left(\frac{AveEconLife_{v=2,y}}{2} - VehAge_{y,t,v=2,a}\right)\right) \cdot VKM_{y,v=2,s} \cdot \frac{V_{y,t,v=2,s}}{V_{y,v=2,s}}$$

Where:

– VKM: vehicle-km

– ε: annual percentage change in mileage as car ages

– AveEconLife: characteristic vehicle service life

– y: year

– t: technology

– v: vehicle type (v=2 is cars only)

– a: vehicle age (0= new, 1 year old, …, 40 year old)

– s: vehicle size

One example of entering transport service demands exogenously into the UKTCM was undertaken in UKERC Energy2050 project, which aimed to show how the UK can move towards a resilient and low carbon energy system over the period to 2050 (Anable et al. 2012). The implications on fuel demand, emissions and the wider energy sector in the UK were modelled through a soft link with a MARKAL elastic demand (MED).

In the so-called Lifestyle variant, the model was used to explore a world in which an important cultural shift has taken place and where travel behaviour would be strongly influenced by concerns relating to health, quality of life, energy use and environmental implications. As a result, travellers would switch to low-energy and zero energy (non-motorised) transport systems. Social norms would "demote large cars, single- occupancy car travel, speeding and air travel", and spatial order would evolve "towards compact cities, mixed land uses and self-contained cities and regions". Technically, this type of scenarios can be imposed by, for instance, lowering the car ownership saturation levels for households owning 2 or more cars, assuming that no "large cars" are being sold, increased consumer preference for low carbon road vehicles etc. (Anable et al. 2012).

b. Version 3.1

Brand, Cluzel and Anable (2017) integrate the findings from Element Energy (2013) into the UKTCM.

The main objective of the analysis in Element Energy Limited (2013) was to assess the current EV market in the UK in terms of the outlook on supply, to examine the main factors influencing vehicle purchase, and to develop a roadmap to the Committee on Climate Change target. With this objective in mind, a choice model was developed to assess the value people place on various aspects of purchasing and owning a car (e.g. up-front costs, size, comfort, running cost, driving range, servicing, performance, infrastructure and charging times). Most of these factors were assumed to remain stable over time.

Element Energy Limited (2013) builds on research that had shown that, in the evaluation of AFV compared to established technologies, consumers have a pay-back period of around 4 years, which is relatively short, and that they may not purchase AFV, even when this makes sense from an economic/lifetime perspective. Moreover, consumers are concerned by driving ranges and long charging times. Consumer awareness of AFV was also found to be relatively low. Finally, the "choice of vehicle segment (e.g. small, medium or large car) was found to be related to the consumer requirements of size, comfort and practicality, whereas brand choice reflects more emotional factors such as brand attachment (loyalty is strong among vehicle buyers), perceived reliability and the buyer's identity construct."

Using recent research that had shown that "attitudinal segmentation is a better predictor of EV acceptance (and hence adoption) than more conventional demographic indicators, including travel patterns" [57], Element Energy Limited (2013) identified 4 segments of the UK new private car buyers:

– 'Enthusiasts', who are prepared to pay a premium for EVs.
– 'Aspirers', who are interested in EVs but concerned by their technical limitations.
– 'Mass market', who are followers of social norms.
– 'Resistors', who are unlikely to buy EVs as they strongly reject their symbolism.

[57] Similar considerations apply to the adoption of fuel cell vehicles.

As discussed before (see ***), the ASCi represent the specific technology preference (positive or negative) not captured by the attributes. For instance, Enthusiasts have a positive willingness-to-pay to drive a new technology – this will appear as a negative ASC.

The 'aspirers' and the 'mass market' consumer are likely to adopt more EV (a) if the supply from trusted brands increases, and the financial and technical barriers are addressed (b) or if the supply of EV increases, respectively. The vehicle attributes represented in the choice model need thus to include both financial and nonfinancial attributes.

Building on this work, Brand, Cluzel and Anable (2017) extended the private buyer market to include 2 segments of company-owned vehicles.

- User-choosers, who consider company-car ownership as primarily an individual purchasing behaviour, their utility calculations are similar to those for private buyers;
- Fleet managers, who are more likely to consider the total cost of ownership (TCO) and practical issues (such as technical suitability) and are less concerned with the brand and image.

In the UKTCM's car choice model, the weighting of attributes can vary across consumer segments, because consumers' opinions on the importance of different vehicle attributes (e.g. running costs) vary.

The key vehicle attributes concerning *private* buyers were: vehicle price, running costs, access to charging/refueling infrastructure, charging/refueling time, driving range, model/brand supply and consumer 'receptiveness' (i.e. technology preference) – most of these attributes are currently a barrier to the adoption of electric vehicles.

Technology preferences were represented by the ASC of the choice model and were based on a regression analysis of empirical data (attitudinal survey and choice experiment) The technology preference parameters (ASCi) were assumed to decrease linearly with increasing sales to represent consumer learning and the neighbour effect.

On the other hand, fleet managers were assumed to approach potential AFV purchase based on TCO (Total Cost of Ownership), model/brand supply and technology suitability (charging access, driving range compatibility) only.

The choice model then follows are decision tree-like structure, where certainty of access to charging (for instance, through home-based overnight charging) and awareness of the existence of the options are a *necessary* condition for purchase. Also, for fleet buyers, necessary conditions for envisaging EVs is that they must have certainty of access to charging/refueling and the range must meet their duty cycle requirement.

7.6. ALTER-MOTIVE

In the context of the EU-project ALTER-MOTIVE, a dynamic partial equilibrium model of the transport sector was developed. It has been applied to analyse the impact of tax instruments and CO_2 emission standards in the passenger car transport market, with a time horizon up to 2030.

This section is entirely based on Ajanovic et al. (2017). The analysis focuses on passenger cars and does not include other transport modes.

Total energy consumption depends on the fuel intensity and the vkm per type of car. The CO_2 emissions are calculated using the fuel specific CO_2 factor.

The model is composed of econometric estimates of the demands for service levels, where 'service level" is a generic term that can refer to new vehicles by category or to vehicle km driven by country and category. Demand is assumed to depend on current fuel prices P, investment costs IC, fuel efficiency and GDP, but also on the demand level of the previous year, which adds a dynamic component.

For instance, the car fleet (V_{stock}) for car type j at time t is modelled as:

$$V_{stock_{jt}} = V_{stock_{jt-1}} + V_{new_{jt}}$$

While new car registration (V_{new}) is calculated as:

$$V_{new\ j_t} = V_{new\ j_{t-1}} \cdot \left(1 + \alpha \cdot \frac{P_{S_{j_t}} - P_{S_{j_{t-1}}}}{P_{S_{j_t}}}\right) \cdot \left(1 + \beta \cdot \frac{Y_t - Y_{t-1}}{Y_t}\right) \cdot \left(1 + \gamma \cdot \frac{IC_{j_t} - IC_{j_{t-1}}}{IC_{j_t}}\right)$$

The model also assumes that, due to technological learning, investment costs for new technologies decline exponentially with time, while no more learning is expected for the mature technology components.

The share of biofuels has been introduced exogenously, but it is not clear how the introduction of other types of alternative fuels has been modelled. Moreover, there is no discussion of how scrappage has been modelled in the car stock module, nor whether endogeneity between car sales and distance driven has been tackled.

7.7. Imaclim-R

Unless stated otherwise, all information in this section comes from Waisman et al. (2012, 2013).

The energy economy-environment (E3) model Imaclim-R 58 belongs to the family of models trying to bridge the gap between bottom-up and top-down models and to introduce to various extent non-energy and non-price drivers of transportation dynamics.

The model combines a dynamic Computable General Equilibrium model of the world economy with bottom-up sectoral modules. It covers the period 2001–2100 in yearly steps through the recursive iteration of annual static equilibria and dynamic modules. "The annual static equilibrium determines the relative prices, wages, labour, value, physical flows, capacity utilization, profit rates, and savings at a year t as a result of short-term equilibrium conditions between demand and supply of goods, capital, and labour markets. The dynamic modules are sector-specific reduced forms of technology-rich models, which take the static equilibria at a year t as an input, assess the reaction of technical systems to the economic signals, and send new input–output coefficients back to the static model to allow computation of the equilibrium for year t + 1." (O Broin and Guivarch 2016)

IMACLIM-R represents the following specific features of the transport sector (a) the strong path dependency of options (b) the influence of non-energy determinants such as the location choices of both firms and households (c) the dependence upon long-lived infrastructure investments.

It takes into account that the saturation of transport infrastructure reduces speed and reduce the attractiveness of specific transport modes[59]. In other words, investments in transport infrastructure[60] capacity influence modal choice, and the model can reflect the effect of changes in these investments. The model also takes into account that, in the absence of intermodal synergies, positive network externalities can make it cheaper to expand one network instead of maintaining two in parallel. This may result in path dependencies and lock-ins in energy-intensive mobility options.

Moreover, the utility function of households contains a "basic need" for mobility which is rather insensitive to fuel prices but reflects constraints following from location choices and the availability of infrastructure, such as the relation between residential areas and work centers in commuting behaviour. It is thus able to incorporate the effect of urban policies aimed at limiting urban sprawl. This spatial distribution follows from trade-offs between (decreasing) transport and (increasing) housing expenditures and is characterised by possibly strong inertia.

In concrete terms, the region-specific "representative" households derive utility from the consumption of goods i above its minimum level, $C_i - C_i^{(0)}$ and from mobility services S_m:

58 The IMACLIM-R model divides the economy in regions and productive sectors. IMACLIM-R also includes transportation with personal vehicles and non motorized transport.

59 The representation of the relation between capacity, transport volumes and speed is an extrapolation of the "macroscopic fundamental diagram" as presented in Geroliminis and Danganzo (2007).

60]. In a review of global transport models by Daky et al. (2014), this is the only study which includes transport infrastructure endogenously as a determinant of travel demand.

$$U = \left[\prod_{goods\ i} \left(C_i - C_i^{(0)} \right)^{\xi_i} \right] \cdot \left(S_m - S_m^{(0)} \right)^{\xi_m}$$

Where:

$$S_m = \left[\sum_{modes\ j} \left(\frac{pkm_j}{b_j} \right)^{\eta} \right]^{1/\eta}$$

Here, the aggregate mobility service S_m is defined as a CES composite of pasengers.km in the four modes under consideration (air, road, public[61], and non-motorized) with the elasticity of substitution between modes η and mode-specific parameters b_j. ξ_m is the elasticity of utility to the level of mobility service.

The model follows the assumption that, besides the standard budget constraint[62], households face an additional constraint, namely a fixed time budget for mobility[63], so that speed gains in specific modes can lead to both increased travel distances and to a shift to faster modes.

This representation of the households' choice problems implies that improvements in the supply of infrastructure (and thus increased travel speeds) can lead to "induced demand". Similarly, increases in energy efficiency (and thus higher fuel) economy can also lead to induced travel (the "rebound effect").

Finally, the freight transport content of production processes is represented by explicit input–output coefficients, but is flexible enough to represent changes in the supply chains, relocation of production infrastructures and a smaller share of "just-in-time" processes.

Assuming almost carbon-free power generation, the diffusion of Electric Vehicles (EV) is a key parameter in the final energy efficiency of private transportation. The model imposes an exogenous maximum on the market share of EV, which reflects initial inertia of the deployment of this technology.

The model decomposes transport carbon emissions along: the carbon intensity of fuels, the energy intensity of mobility, the modal structure of mobility and the volume of mobility.

Following Dargay et al (2007), it is assumed that the motorization rate in each region of the model is related to per capita disposable income with a variable income elasticity in function of income levels. For the highest levels of income, the elasticity decreases progressively to represent equipment saturation so that the motorization rate never exceeds the current US value (0.7 vehicle per person).

The fleet is composed of different generations of vehicles, grouped according to the year in which they were put into service and the transport technology.[64]

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[61] The model does not differentiate between inter- and intra-city trips, so "public transport" includes both urban public transports (buses, metros, etc.) and inter-city trains.

[62] The fixed costs of car ownership do not enter into the budget constraint for day-to-day mobility decisions, but are considered in households' investments.

[63] As discussed for instance in Schäfer and Victor (2000).

[64] http://themasites.pbl.nl/models/advance/index.php/Transport_-_IMACLIM#scite-92ec968b02730aeb369e017f26410a66

Transport technologies are included at a rather aggregate level: “electric vehicles” represent implicitly all types of vehicles that use electricity as service provider, including fuel cells and hydrogen vehicles. Technologies are differentiated by their unitary fuel consumption and their capital costs. It is assumed that capital costs decrease endogenously in function of the learning-by doing process.

Total sales are obtained as the difference between the forecast for the total fleet and the remaining vehicles of previous vintages. Choices between the transport technologies are modelled with a logit function, where costs are modelled under myopic expectations (i.e. households are assumed to believe that fuel prices will remain constant)[65].

O Broin and Guivarch (2016) have used the model to demonstrate complementarities between restricting infrastructure deployment and carbon pricing.

65 http://themasites.pbl.nl/models/advance/index.php/Transport_-_IMACLIM#scite-92ec968b02730aeb369e017f26410a66

7.8. SULTAN

The SULTAN (SUstainabLe TrANsport) has been developed by Ricardo-AEA on behalf of the European Commission to explore transport decarbonisation scenarios.

The SULTAN model has been implemented in Excel (Hill et al. 2010). EU transport is split in 7 passenger modes and 6 freight modes, with up to 10 powertrain options, including both conventional and alternative fuels. Most data for the BAU scenarios originated from TREMOVE, EC ExTREMIS and the UK MARKAL-ED model. One of the motivations for the development of SULTAN was to deal with some of the limitations of TREMOVE, such as its limited time horizon (up to 2030[66]), and the non-inclusion of "a number of future powertrains and energy carriers that are expected to become important in the timeframe to 2050 (such as fuel cell, battery electric and plug-in hybrid vehicles)". Compared to other models, SULTAN is relatively simple. As a result, the calculations are easy to understand and transparent. According to the authors, the "data have large ranges of uncertainty attached to them, which are likely to negate any increase in accuracy gained by more complex modelling techniques."

Some of the most relevant simplifications are that (a) the average lifetime of every vehicle in each mode is assumed to be the same (b) every vehicle in each mode travels the same distance each year, whatever its powertrain (c) every vehicle is assumed to undertake the same type of journey (d) there is no variation between the characteristics of vehicles of the same mode, powertrain and vintage year.

The stock model is very simple. For each possible scenario, the vehicle stock in future years is modelled as a percentage change compared to the stock in the BAU scenario. New vehicles are calculated as a residual, by subtracting the surviving vehicles in all previous vintage years from the total number of vehicles in the fleet in a given future year. The survival rate is defined for each future year and vintage.

The projections of demand (in vkm or tkm) and the vehicle stock are not linked by calculation in the model – any interaction between these two parameters needs to be introduced explicitly by the user.

The model also assumes that the capital costs of any powertrain will decrease as a function of the cumulative sales of this technology.

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66 In the meanwhile, the time horizon of TREMOVE has been extended to 2050.

7.9. MINIMA-SUD

Zachariadis (2005) describes a transport simulation and forecast model which was developed under the MINIMA-SUD (Methodologies to Integrate Impact Assessment in the Field of Sustainable Development) project of the 5th Framework Programme on Research and Technological Development of the EU. The model covers the whole transport sector (road and rail transport, inland shipping and aviation) in the 15 EU Member States in the beginning of 2004. It belongs to the class of models that bridge "the gap between top-down energy-economy models, which address the transport sector in an aggregate fashion, and bottom-up technological models, which provide sufficient technological coverage but often cannot simulate the effect of behavioural changes induced by changing costs and income."

The **demand module** simulates the evolution of total transport activity, expressed in pkm for passenger transport and tkm for freight transport, year by year up to 2030. The main drivers are demographic, macroeconomic and energy price variables on the one hand, and the generalised costs of transport on the other hand. In order to estimate the time costs in equilibrium, total time spent driving for vehicle type *m* is calculated with the following congestion function, which is different for each road type:

$$traveltime_{m,t} = traveltime_{m,2000} \cdot \left(\frac{vkm_{m,t}}{vkm_{m,2000}}\right)^{g} \cdot \left(\frac{invex_{t,s}}{invex_{t,b}}\right)^{-h} \cdot \left(\frac{parkex_{t,s}}{parkex_{t,b}}\right)^{-i}$$

invex and *parkex* are the investment expenditures in road infrastructure and parking space, respectively. *r* is a country-specific residual adjustment to address other effects not covered explicitly in this function, and the index 2000 refers to the base year. *b* and *s* denote baseline and scenario situations, respectively. The elasticities in this function are based on a combination of literature study and expert judgement.

Note that the "investments in parking space may improve or deteriorate congestion, depending on the combined effect of at least two decisive factors: the equilibrium between parking demand and supply, and the availability of substitutes for road travel."

Modal shares are estimated according to a nested utility CES function for consumers, and a nested CES cost function for producers. The approach used is close to the one used in the TREMOVE model. Equilibrium between transport supply and demand is obtained in an iterative algorithm.

For road transport, the model also calculates the **evolution of the vehicle stock and distance travelled**. The vehicle stock is obtained from the pkm/tkm calculated in the previous step, combined with assumptions with respect to the annual mileage and load factors.

The stock is further split into age cohorts, according to an initial exogenous age distribution in the base year and assumptions on the evolution of scrapping rates. The standard modified Weibull function for the survival probability, $\phi(k)$ (where b and T are estimated country-specific parameters):

$$\varphi(k) = e^{-\left(\frac{k+b}{T}\right)^{b}}, \varphi(0) \equiv 1$$

is complemented with parameters to simulate the impact of income effects and scrapping schemes to obtain the number of vehicles scrapped during year t:

$$SCRAP_t = \sum_{k=1}^{29} \left[STOCK_{t-1,k-1} \cdot \left(1 - \frac{\varphi(k)}{\varphi(k-1)} \right) \right] \cdot \left(\frac{INCOME_t}{INCOME_{t-1}} \right)^{\gamma} \cdot \left(\frac{C_{t,s}}{C_{t,b}} \right)^{-\delta}$$

with C the total lifetime cost of a new car, and b and s indices denoting the baseline situation and a scenario, respectively.

For road transport, the **shares of vehicle technologies** are estimated in two steps.

First, the shares of the fuel/size groups are determined according to the following relationship:

$$sh_{j,t} = \frac{w_{j,t}\left(ATC_{j,t}\right)^{-2}}{\sum_j w_{j,t}\left(ATC_{j,t}\right)^{-2}}$$

with *sh* the share of fuel/size group j in a given year, *w* a dimensionless 'maturity factor', which is used to simulate technology availability as well as consumer preferences not attributable to costs, and ATC the annualised real travel costs. The maturity factors are calculated through a combination of extrapolations of past developments and expert knowledge on the future evolution of these shares.

Second, the shares of each fuel/size group are allocated to those technologies that are assumed to be commercially available within this particular group in the given yea

For non-road transport modes, potential future improvements in fuel efficiency and emissions behaviour are assumed in accordance with the technical literature. Vehicle fleet turnover is simulated implicitly.

7.10. CIMS

CIMS[67] is an integrated, energy-economy equilibrium model that simulates the interaction of energy supply-demand and the macroeconomic performance of key sectors of the economy, including trade effects. It has been developed by the Energy and Materials Research Group (EMRG) at Simon Fraser University, in Canada.

As CIMS is not a general equilibrium model, it does not take into account government budget constraints, or equilibria in factor markets (employment and investment). Its representation of input-output relation is skewed toward energy supply, energy intensive industries, and key energy end-uses in the residential, commercial/institutional and transportation sectors (Jaccard 2005).

The remainder of this section is based on Rivers and Jaccard (2005), Horne et al. (2005) and Axsen et al. (2009).

CIMS tracks the evolution of technology stocks over time through retirements, retrofits, and new purchases, with consumers and producers making sequential decisions with limited foresight. CIMS simulates choices at service demand nodes, for instance representing the demand for heated commercial floor space or for person-kilometres-travelled. CIMS calculates energy costs (and the corresponding GHG) at each service demand node.

The model starts with total stocks in a base year. If these stocks are split in vintages, the model determines when each vintage retires in the future. If not, a linear function (driven by time) causes a certain percentage of existing stocks to retire each year - consistent with economic life expectancies. In each of these future years, the output capacity of the surviving stocks[68] is subtracted from demand in that year (for say steel) to calculate how much new stock must be acquired in that year to meet total demand. The forecast for service demand can be either exogenous or the result from the interplay of the energy supply-demand module with a simplified macro-economic module. In the transport module, the load factor and the annual distance driven per vehicle are assumed constant [69].

There are also two special cases[70]:

- Rapid change in energy prices (for instance because of rapidly rising carbon taxes) can cause accelerated depreciation. The “retrofit function” in the model compares the operating costs of surviving stocks with the life-cycle costs (annualized capital plus operating) of new stocks. The retrofit function will then automatically retire (probabilistically) some of the surviving stocks and replace these with stocks selected in the new stock calculation. The more extreme the cost difference between new stock life-cycle cost and surviving stock operating cost, the more of the surviving stock that gets retired.
- If demand in a future year falls below surviving stocks (perhaps because of rapidly rising carbon taxes that cause a quick contraction in demand from some industries), the model retires more of the surviving stock than would have been retired by time alone. There is no new stock in this case.

[67] CIMS stood originally for Canadian Integrated Modeling System. As the model has also been applied to other countries, the acronym is now treated as a proper name (Jaccard 2005).
[68] Derived from service demand using constant load factors.
[69] E-mail from Mark Jaccard, 17 May 2017.
[70] E-mail from Mark Jaccard, 17 May 2017.

In a given node; thousands of technologies can compete for market share. The passenger vehicle node considers both technologies powered by gasoline and alternative fuels.

For a given period, the market share of a technology *j* is determined using a function that considers both the financial costs and intangible costs of *j*. For instance, in the case of passenger transport, there is an intangible cost associated with public transport due to real or perceived inconvenience, lower status, longer travel time[71], discomfort, etc.

The lifecycle cost (*LCC*) of *j* is:

$$LCC_j = \left[\left(CC_j + i_j\right) \cdot CRF + MC_j + EC_j\right]$$

where CC_j is the initial capital cost, i_j is the *perceived* intangible cost, *MCj* is the annual maintenance costs, and EC_j is the annual energy cost of j. The cost recovery factor, *CRF*, is used to annualize upfront costs (CC_j and i_j), calculated as:

$$CRF = \frac{r}{1 - (1 + r)^{-n_j}}$$

where r is the *perceived* discount rate of the decision maker, and n_j is the lifespan of technology j. The discount rate is usually the same for all technologies *at a given node*, but can differ between nodes according to empirical research

The market share[72] of technology *j*, MS_j, relative to a technology set *K* in a given node is determined as follows:

$$MS_j = \frac{{LCC_j}^{-v}}{\sum_{k=1}^{K} {LCC_k}^{-v}}$$

The *v* parameter is an indicator of market heterogeneity. A high *v* parameter indicates that consumers have relatively uniform preferences. In this case, a technology with a lower *LCC* will capture almost the entire market. In contrast, a low *v* implies a relatively even distribution of the market shares for a technology set, even with substantial differences in *LCC* values. Thus, the *v* parameter also dictates the sensitivity of the model to cost changes.

CIMS has the capability to represent neighbour effects with the i_j parameter, following the declining intangible cost function.

$$i_j(t) = i_{fixed} + \frac{i_{Var}(0)}{1 + A \cdot e^{k \cdot MS_{t-1}}}$$

where $i_j(t)$ is the intangible cost of technology j at time t, i_{fixed} is the portion of initial intangible cost that is static, $i_{Var}(0)$ is the variable portion of intangible cost in time period zero, MS_{t-1} is the market share of the technology in the previous simulation period ($_{t-1}$), and the *A* and *k* parameters represent the curve and rate of change of the intangible cost in response to increases in technology market share. This intangible cost curve and the *v* and *r* parameters have been estimated using discrete choice models.

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71 This seems to imply that CIMS does not take into account the monetary value of time spent in transit.

72 This represents the share of the technology in annual sales, not in the total stock. E-mail from Mark Jaccard, 17 May 2017.

Originally, the behavioral parameters of the model have been estimated through a combination of literature review, judgement, and meta-analysis. However, using separate estimates of these parameters has led to consistency problems. The current practice is now to empirically estimate the key parameters simultaneously from empirically derived choice models designed specifically to mesh with the existing CIMS structures. We now provide some examples.

To the best of our knowledge, Rivers and Jaccard (2005) is the first use of choice models to estimate the parameters of CIMS. They used a choice experiment to gather data on the choices made by industrial plants with regard to steam generating technologies.

The maximum likelihood parameters for the MNL model were then used to estimate the CIMS parameters., using the following formula, which relates how the market shares in new sales, calculated with a MNL model (on the left-hand side) relate to those calculated with CIMS (assuming that both models pertain to the same technology set).

$$\frac{e^{U_j}}{\sum_{k=1}^{K} e^{k}} = \frac{\left[CC_j \cdot \frac{r}{1-(1+r)^{-n}} + OC_j + i_j\right]^{-v}}{\sum_{k=1}^{K}\left[CC_k \cdot \frac{r}{1-(1+r)^{-n}} + OC_k + i_k\right]^{-v}}$$

In both approaches, a technology’s market share follows a sigmoid shape curve (Horne et al. 2005).

In this formula, the discount rate can now be isolated. Indeed, as demonstrated by Train (1993, 2002), the implicit discount rate applied by a consumer can be determined by comparing the capital cost parameter with the annual cost parameters[73]: $r = -\frac{\beta_{CC}}{\beta_{AC}}$, where β_{AC} is a parameter representing the importance of all annual costs together.

The (annual) intangible cost parameter can then also be calculated by comparing any non-cost parameters of the MNL model to the annual cost parameters. This parameter then represents the monetary cost of the intangible (non-financial) qualities of each technology: $i_j = -\frac{\beta_j}{\beta_{AC}}$

The final CIMS behavioral parameter (v), representing the degree of heterogeneity in the market, is roughly equivalent to the “scale” of the MNL model (see Train (2002) for a discussion of model scale). Despite the similarities between the CIMS and MNL models, there is no direct equivalence between the CIMS heterogeneity factor and the scale of the MNL model. Rivers and Jaccard (2005) have therefore used ordinary least squares (OLS) to find the value of v that corresponds to the scale of the MNL model, so that the predictions from both models are consistent over a broad range of scenarios.

Similarly, Horne et al. (2005) have used stated preferences to estimate the parameters in a MNL model. In order to estimate the parameter v, Horne et al. have programmed a solver routine to find a v that minimized error between the left and right side of the equation for different attribute value combinations.

An additional complication was that the technologies in the choice experiment did not correspond to the (wider set of) technologies available in CIMS.

[73] Note that this only holds under the assumption of perfect foresight and rationality.

As explained by Horne et al.:

> "The new vehicle types were given the same attribute coefficients, but the alternative specific constants (ASC) were chosen to reflect differences in vehicle types. For example, the ASC for diesel vehicles was set as the average of gasoline and alternative fuel vehicles, indicating that it was slightly less preferred than the gasoline option, but more so than less conventional automotive fuels. Selecting an ASC for electric vehicles was somewhat problematic because the driving range and recharging time are both significant attributes for this type of vehicle (Bunch et al., 1993) that were not tested in this research. A modifier for the ASC was scaled from the work of Ewing and Sarigollu (2000), assuming a driving range of 160 km, and a recharging time of 40 min."

A specific concern with the use of ASCs to match existing market shares, is that ASCs may dominate the impact of the alternatives' attributes. Therefore, Horne et al have assigned "a variety of attractive and unattractive attribute values (…) to the different alternatives to see what range of market share predictions could be produced for each alternative".

Mau et al. (2008) extend this approach to capture dynamics in Canadian consumers' preferences for new vehicle technologies (hybrid gas-electric vehicles (HEVs) and hydrogen fuel cell vehicles (HFCVs)), and demonstrate how their results provide behavioural parameters for CIMS.

Mau et al. (2008) emphasize that, as these are new technologies, revealed preferences cannot be estimated from past behaviour. However, even with stated preferences, it is important to acknowledge important differences between the two types of technologies:

– HEV are 'evolutionary technologies': they provide the same service as a mainstream technology without requiring major changes in infrastructure or a significant amount of learning by the consumer.

– HFCV are 'disruptive innovations': they possess attributes initially unfamiliar to consumers and producers, perhaps requiring major changes to infrastructure and institutions as well, with the potential to shift market structures and induce behavioural change.

The study tested two hypotheses: (a) people's value for hybrid gas-electric and hydrogen fuel cell vehicles change as the number of people owning these types of vehicles increase (the 'neighbor effect') (b). the neighbor effect differs between evolutionary and disruptive technologies.

This study is similar to Axsen et al. 2009.

7.11. New Zealand NLTDM

The development of the New Zealand National Long-term Land Transport Demand Model (NLTDM) is discussed in Stephenson and Zheng (2013), on which the rest of this section is based. The model evaluates transport demand scenarios for up to 30 years. The key objective of the model is to describe how transport demand *might* evolve over time, rather than to provide point estimates; it is not meant as a forecasting tool for short-term fluctuations in demand.

In order to build the projections, transport demand was broken down into three different components:

– trends and patterns due to path dependencies, such as population growth, age structure and location; economic growth and vehicle fleet turnover

– deviations from trend path dependencies due to relative price shocks (mainly of fuel prices) and income effects;

– temporal interdependencies; such as the co-movement of industry growth and the transmission of shocks over time.

While the authors sought to produce a database on empirical estimates of the drivers of transport demand, they found large gaps in the literature for which they had to make assumptions. Moreover, many studies estimated demand relationships for individual modes, without considering the possible substitutes. Model parameters based directly on existing literature could therefore lead to double counting. Moreover, there was considerable variation in empirical estimates.

The probability that a household would own one, two, or three or more vehicles was estimated with a logit model. Explanatory variables included real household income, the density of the region of residence, the average age in the household, and whether or not the household lived in the capital.

The 'Vehicle fleet' submodel projected numbers of vehicles by age, class, and motive technology or fuel type. It was assumed that the fleet (v) evolves according to a transition matrix W, which varies by technology type (i) and varies over time. W describes rates of entry to the vehicle fleet (M) and age-specific scrappage rates (S):

$$v_{it} = W_i \cdot v_{i,t-1}$$

$$W_i = \begin{bmatrix} M_1 & \dots & M_i & \dots & M_k \\ S_1 & 0 & 0 & \dots & 0 \\ 0 & \ddots & 0 & \dots & 0 \\ 0 & 0 & S_i & \dots & 0 \\ 0 & 0 & 0 & S_{k-1} & 0 \end{bmatrix}$$

The model has 2310 different types of vehicles in it. The vehicle characteristics included pertained to the vehicle class, the fuel types (including hybrids and EV), and vehicle vintages.

Scrappage rates were projected for each vehicle type in a deterministic fashion based on past scrappage rates. For each vehicle class and year, the number of vehicles newly entering the fleet, whether new or used, was then modelled as a function of replacement demand for a particular class of vehicle plus additional demand to meet growing demands.

The growth in demand for (non-bus) passenger vehicles was based on the previously estimated growth in household vehicle demand. For heavy commercial vehicles, growth in vehicle demand was based on the forecasted growth in road-freight tonne-kilometres, assuming no change in average tonne-kilometres per vehicle over the long term. Finally, demand for buses was assumed to grow with employment (as proxy for growth in peak demand for public transport).

For light vehicles, a logit model was used to model the shares of 'newly purchased' incoming vehicles and (imported) second hand vehicles. To model the age distribution of second hand vehicles, a Poisson model was used, combined with a normally distributed trend growth rate in the average age of used import.

The share of newly registered vehicles that were alternative-fuel vehicles was modelled based on logistic growth curves and *exogenous* assumptions about the shares of registrations in the long term. Finally, exogenous assumptions were also used to split AFV in electric vehicles and plug-in hybrids, with the share of hybrids in registrations of alternative-fuel vehicles declining over time.

The projections of vehicle-kilometres travelled were based on the historical average vehicle-kilometres travelled per vehicle, by vehicle type and age, while changes in kilometres travelled per vehicle were based on changes in the costs of travel and growth in incomes. For bus and freight vehicles, it was assumed that kilometres travelled per vehicle depend only on demand for these services.

In order to obtain projections of passenger-kilometres, the model uses region-specific occupancy but exogenous occupancy rates.

Emissions were calculated by multiplying fuel use by emissions factors.

For households, the demand projections were subsequently adjusted to account for the propensity of different age groups to use different forms of travel (public transport, vehicle travel and vehicle passenger or non-driver travel).

7.12. Irish models of car ownership

The Irish National Transport Authority's (NTA) Regional Modelling System is composed of a National Demand Forecasting Model, five detailed regional transport models (RMS) and Appraisal Modules covering the entire national transport network. As there is no disaggregation of the car stock according to powertrain and/or fuel type, it will not be discussed here.

A somewhat different approach has been used by Hennessy and Tol (2011), to estimate not just the size, but also the composition of the car stock, according to fuel, engine size and age.

Their model also uses the concept of "saturation point", where changes in "changes in the car total stock are directly proportional to the changes in the population or its demo-graphic components." This saturation rate is set at 0.8 cars per adult population. Until the saturation point is reached, the forecast of the car stock *C* at time *t* is given by the following model with error correction:

$$\Delta \ln \frac{0.8}{C_t/P_t - 1} = \alpha + \beta \frac{Y_t}{P_t}$$

The next step is to predict the engine size. Hennessy and Tol distinguish 9 categories of car size and estimate the income elasticity for each engine size and fuel type. In order to forecast the future shares of diesel cars, they use a breakeven distance methodology along with information on the mileage distribution by engine size. The mileage distribution data confirm "that there are clear differences in the driving profiles of the different engine classes".

The car demographic model distinguishes 10 engine sizes and 25 age classes. The dynamic equations are:

$$\begin{cases} C_{t,1,s,f} = S_{t,1,s,f} \\ C_{t,a,s,f} = (1-\rho_{t,a,s,f})C_{t-1,a-1,s,f};\, a = 2,3,\ldots,4 \\ C_{t,24,s,f} = (1-\rho_{t,24,s,f})C_{t-1,24,s,f} + (1-\rho_{t,25,s,f})C_{t-1,24,s,f} \end{cases}$$

where $C_{t,a,s,f}$ is the stock of private cars in year *t*, of age *a*, of engine size *s* and of fuel *f*; *S* is the sales, and $\rho_{t,a,s,f} = 1 + \frac{0.015\cdot(a-1)}{1+0.03\cdot(a-1)}$ is the probability of scrapping which is independent of time, size and fuel. It is assumed that the scrappage parameter is time invariant. All relationships are estimated with the use of historical data.

The forecasts for distance D_t is given by:

$$D_{t=1} = \left[1 + \varepsilon_{i,t}\left(1 - \frac{P_{t+1}}{P_t}\right)\right] \cdot D_t \cdot \Delta \frac{C_{i,j,t}}{C_t}$$

where C_{ijt} is the number of cars of size i and fuel j at time t; $\varepsilon_{i,t}$ is the price elasticity of distance travelled for engine size *i* in time period *t*.

Hennessy and Tol have run a series of scenarios with different assumptions regarding future electric car sales and their fuel efficiency. A key limitation of the model, as admitted by the authors, is that the model cannot predict endogenously what type of conventional vehicles are replaced by the electric ones.

7.13. Austrian national models

The Austrian Energy Agency has developed the dynamic vehicle fleet model SERAPIS (Simulating the Emergence of Relevant Alternative Propulsion technologies in the car and motorcycle fleet Including energy Supply) in order to analyse some critical aspects concerning market success of electric vehicles. It relies on stock flow modelling and the Systems Dynamics software Vensim®.

The number of vehicles in a scenario k at year t, $N_k(t)$, is based on a linear elasticity model which modifies the number of vehicles relative to a baseline scenario (k = 0):

$$\frac{N_k(t) - N_0(t)}{N_0(t)} = e \cdot \frac{C_k(t) - C_0(t)}{C_0(t)}$$

$C_k(t)$ represents the costs of owning a vehicle in scenario k at year t, and e is the price elasticity.

A multinomial logit model is used to calculate the propulsion technologies chosen for these new vehicles, which include electric, hybrid and internal combustion engine for cars and electric and internal combustion for motorcycles. In SERAPIS the utility U_i of propulsion technology i is a function of the investment costs I_i, the operating costs O_i, the variety of makes and models M_i, the density of service stations D_i and the range with a single tank contents Ri (Pfaffenbichler et al. 2011).

Kloess and Müller (2011) investigate the effects of policy, fuel prices and technological progress on the Austrian passenger car fleet in terms of energy consumption and greenhouse gas (GHG) emissions.

The car fleet is modelled from a bottom-up perspective, with a detailed coverage of vehicle specifications and propulsion technologies, combined with top-down demand models.

Although the model only covers the passenger car fleet, it does take into account that individuals can switch to other modes if the cost of passenger car transport increases. The only input parameters are prices and income, implicitly assuming the road and public transport infrastructure are on a high level, and are not important drivers of possible modal shifts.

The model is composed of four modules.

The first module is the **vehicle technology model** where different vehicle powertrain options are modelled bottom-up to analyse the influence of technological progress on their costs.

The second module derives **market shares of technologies** based on their specific service costs. In order to represent the heterogeneity in consumer preferences[74] and knowledge, a multinomial logit model has been used with specific service costs as the main decision criterion. Diffusion barriers are also included in the model to represent the specific competitive disadvantages of alternative propulsion technologies, such as limitations in performance characteristics, inadequate infrastructure, or a small range of car models available with the desired propulsion technology. These barriers are summarized in an index that enters the utility function.

[74] The authors even consider the possibility of consumer groups who are willing to pay for an advanced vehicle technology, which is environmentally benign even if it is not the best economic option.

The third module covers the **influences of income, fuel prices and fixed costs on the fleet size, the average annual driving distance and the transport service level** (in this curb weight and engine power).

The number of vehicle *registrations* per year t, CAP_t, is represented as a function of the fuel price *FP*, fixed costs *CC* and gross domestic product *GDP* (where the α represent the respective elasticities):

$$\frac{CAP_t}{CAP_{t-1}} = \left(\frac{FP_t}{FP_{t-1}}\right)^{\alpha_{FP}} \cdot \left(\frac{CC_t}{CC_{t-1}}\right)^{\alpha_{IC}} \cdot \left(\frac{GDP_t}{GDP_{t-1}}\right)^{\alpha_{\gamma}}$$

Similarly, distance travelled D is represented as function of fuel prices and GDP:

$$\frac{D_t}{D_{t-1}} = \left(\frac{FP_t}{FP_{t-1}}\right)^{\omega_{FP}} \cdot \left(\frac{GDP_t}{GDP_{t-1}}\right)^{\omega_{\gamma}}$$

The model distinguishes three categories of vehicles: compact class, middle class and upper class, which are defined by mass and engine power. The service factor F_t represents average mass and engine power of cars sold, and is determined by Income and fuel prices:

$$\frac{F_t}{F_{t-1}} = \left(\frac{FP_t}{FP_{t-1}}\right)^{\beta_{FP}} \cdot \left(\frac{GDP_t}{GDP_{t-1}}\right)^{\beta_{\gamma}}$$

The fourth module is a **bottom-up fleet model** of the Austrian passenger car fleet. The fleet is modelled in detail considering age structure, user categories and main specifications of the cars (e.g. engine power, curb weight, propulsion technology, specific fuel consumption, GHG emissions, etc.).

Taking into account the inertia in the regeneration of the car fleet, the actual fleet CAP_t is determined by the surviving cars of all the previous 30 generations. The annual decommission of cars is determined by the likelihood of mechanical failure modelled through a Weibull distribution.

Based on the fleet model the total energy consumption and the GHG emissions are determined, with a differentiation between tank-to-wheel (TTW) and WTW energy balances and emissions.

7.14. DYNAMO

MuConsult describe the DYNAMO (Dynamic automobile market model) model[75].

The model can be used for both short-term and long-term forecasts of the size, the composition, the costs and the use of the Dutch vehicle stock. The model can be used in isolation, or jointly with the Dutch national[76]. and regional traffic models.

The so-called "base matrix" or "automobile household (AH) matrix" in DYNAMO represents the evolution of the joined distribution of household types and car types. The 128 household types are defined according to socio-demographic data, while the 150 vehicle types are differentiated according to the following criteria: the age of the car, its fuel type, its weight and ownership (private or company-owned). Th AH matrix describes car ownership in a given year for each household type.

The model is composed of several modules to describe the evolution of car ownership:

– D (Household). This module determines the exogenous change in the number of households per household type.
– D (Car use). This module determines the number of kilometers driven for each purpose (commuting, business, other), the average number of kilometers driven per household and the number of kilometers driven per car type. The representation of policies that can affect the variable costs of cars is part of this module.
– Scrapping and accidents. The probability that the car will not be scrapped and will therefore remain in the active car fleet for another year is determined per car type. Using vehicle registration statistics, a fixed percentage of all cars, randomly distributed among all vehicle types, are removed from the car fleet annually as a result of accidents. For cars under 10 years of age, the model assumes that the probability of being scrapped is fixed. For older cars, this probability of being scrapped was assessed using a multinomial logit function which includes the residual value of the car, subsidies for scrapping and repair costs as features. As we will see below, this residual value (the price on the second hand market), is endogenous to the model and is used in an iterative procedure to balance supply and demand.
– ImExport. Dynamo assumes a constant sum of imported and exported cars for each car type.
– HHNumber. This module uses a nested logit model (with the top nest relating to decisions of whether to have a car) to determine (for each time period) the number of cars (0, 1, 2, or more than 2 cars) in each household type. The logit model uses both data on the household characteristics and the average costs of cars.
– DHHLease. This module determines (for each time period) the number of leased/company-owned cars for each household type. The total number of leased cars is left exogenous in the model. For these cars, the costs are borne by the employers unless the user wants to drive a vehicle that is more

[75] The most recent model documentation is available in Dutch only. The most recent English summary we are aware of is Meurs et al. (2013).

[76] http://www.mkba-informatie.nl/mkba-voor-gevorderden/richtlijnen/modelbeschrijving-lms-2000/

expensive than the one offered by the employer. Moreover, household income must be revised upward to reflect for the income in kind provided by the company car. Furthermore, the distribution of new leased/company owned cars over types is determined.

- Type choice. This module determines (for each time period) the distribution of *privately* owned vehicle types for each household type. A multinomial logit model based on combined SP–RP data was used to estimate the type choice model. A variable reflecting the number of vehicle models available for a particular car type is also included, because a higher variety in a given class increases the attractiveness of that class (see McFadden 1978).
- Environment. The output of this module are the emissions of local pollutants produced by the car fleet.
- CO_2 module. This disaggregates the vehicle types into emission categories using a disaggregate logit with the same variables as the DHHLease and Type choice modules. This detail is needed because under the Dutch car taxation system, the taxation is increasingly based on CO_2 emissions.
- The EMOD module adjusts the prices of second-hand cars to match supply and demand in the model in an iterative approach where prices of new cars are left exogenous. It is assumed that there is a time-lag in the reaction of demand to changes in the market prices.

The DYNAMO model has been used as an input to the Dutch National Model System

The model also contains modules for alternative fuel vehicles (AFV). These modules do not affect the total fleet, only its composition. Alternative fuel vehicles are compared to ICE vehicles of similar sizes. The ASC are modified through time to represent that AFVs "converge" to ICE vehicles.

7.15. TREMOVE model

TREMOVE is a transport and emissions simulation model developed for the European Commission, designed to study the effects of different transport and environment policies on the emissions of the transport sector. It estimates the transport demand, the modal split, the vehicle fleets, the emissions of air pollutants and the welfare level under different policy scenarios (De Ceuster et al. 2007).

It is a partial-equilibrium model for the demand and supply of transport services, where the generalised cost of transportation (including the opportunity cost of time) is used as the demand price.

The model has been linked with the PRIMES energy systems model. It can run either as a stand-alone tool or fully integrated in the rest of PRIMES. In the integrated run mode, the transport model takes the projection of fuel prices from PRIMES, while the transport model transmits projections of fuel, electricity and hydrogen consumption to the rest of PRIMES model. The model linkage is also used for life cycle analysis of emissions of fuels used in transport, and can cover the entire well to wheel calculations. The PRIMES-TREMOVE Transport model can also link with TRANSTOOLS, a network transport model with spatial information (E3MLab 2013-2014).

The model has been designed with a focus on long-term simulation (up to 2050) – it therefore includes technologies and fuels such as the electrification of road transport, high blending of bio-fuels in all transport sector and market penetration of a wide range of alternative fuels including hydrogen. Not all technology and fuel options are available immediately: they become available gradually over time and reach commercial maturity at various degrees and at different future times, depending on market uptake (E3MLab 2013-2014).

Before we describe the current version of the model, we briefly discuss the vehicle stock module as described in De Ceuster et al. (2007). For all road vehicles, the stock for each year was estimated as follows:

– For each vehicle category (e.g. cars), the stock per vehicle category surviving from the previous year was calculated. The survival functions in the scrappage module followed the usual Weibull distributions.

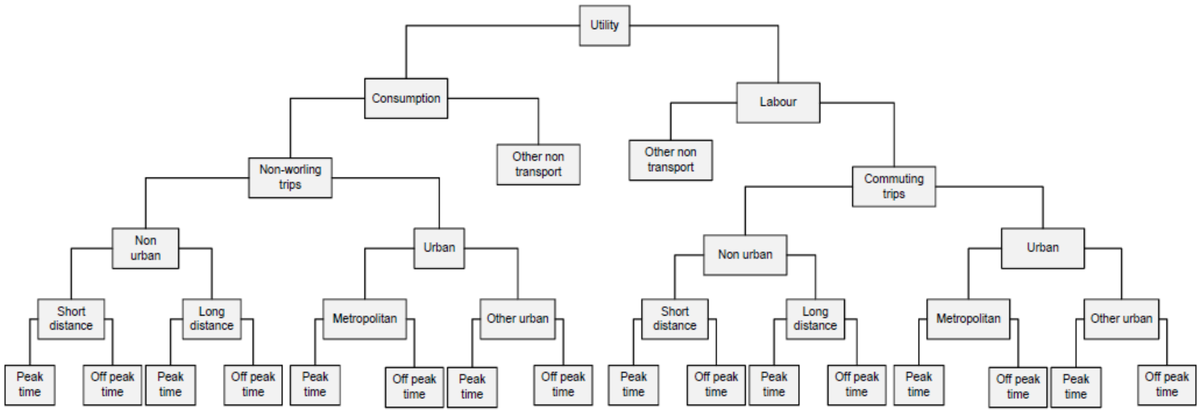
– The demand module of the model yields the demand for vehicle-km in a given year. This was converted into the number of vehicles needed to fulfil this demand, based on the average historic (and thus exogenous) mileage of the vehicle category (e.g. cars). The difference between the desired stock and surviving stock resulted in the sales of new vehicles (cars) in year t.

– The calculated number of new vehicles *per category* was then further split into vehicle *types* with a nested logit model of purchases.

– The annual mileage per vehicle type depends on the category average, on the type under consideration and on the vehicle's age. Combining this information with the fleet age structure obtained in the previous steps lead to an estimate estimate, for each type and technology, the number of vehicle-km driven.

The rest of this section is based on the model description in E3MLab (2013-2014).

The **transport demand** module simulates mobility decisions driven by exogenous macroeconomic variables. Private passengers are assumed to maximise utility under budget and other constraints, while firms are assumed to minimize costs for a given production level. Utility is represented by a nested Constant Utility of Substitution (CES° function, with the decision between consumption and leisure at the root of the tree. The representation of the cost function for firms is similar.



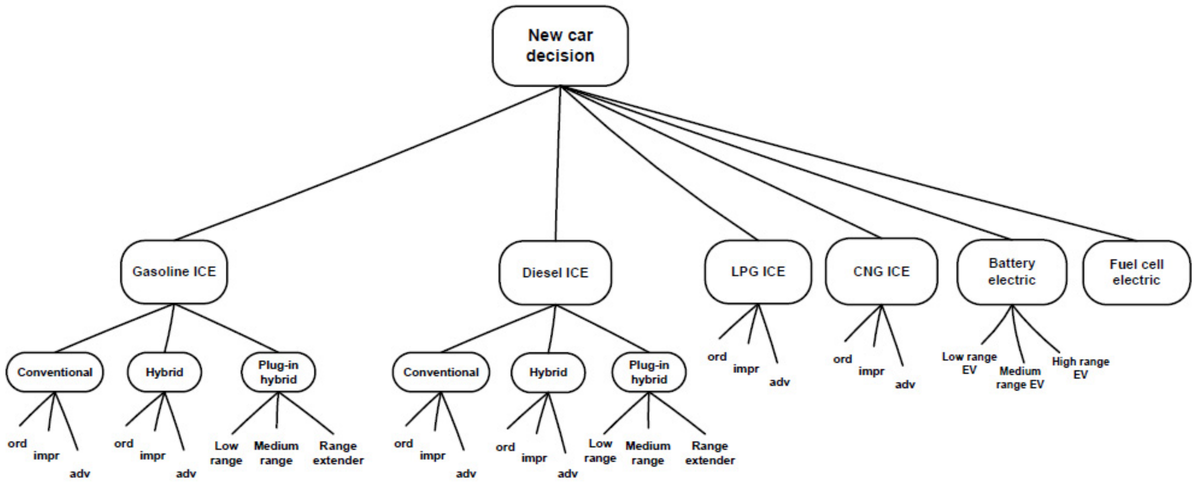
The deeper branches of the tree (not visualised here) represent the choices between transport modes and road types.

The parameters of the CES are calibrated at the hand of historical data. The elasticities of substitution are mostly small, implying limited possibilities for modal shifts. However, the current version of the model is flexible enough to represent that new policies (such as investments in infrastructure and intelligent transport systems) lead to a higher potential for modal shift by modifying the elasticities.

The **supply side** of the model contains stock of the transport means (vehicles, trains, vessels, aircrafts) inherited from previous time periods, calculates scrapping due to technical lifetime, evaluates the economics of possible premature scrapping and determines the best choice of new transport means which are needed to meet demand. The fuel mix is also chosen endogenously.

The purchasing costs of new technologies and new car components change through time according to learning curves that depend on cumulative sales and on technology support policy. Non-monetary costs (such as the technical risk of yet immature technologies, acceptance factors representing market penetration and the density of refuelling/recharging infrastructure for AFV) on the one hand, and imitation and social learning effects on the other hand are also represented in the model. For instance, it is assumed that consumers and firms compare the range possibilities of each vehicle technology with the availability of refuelling/recharging infrastructure for all classes of trip types and trip distances. If there is a mismatch between the distribution of trip distances, the technically feasible range and the density of refuelling infrastructure, this is represented as a cost.

The choice of technology and fuel type when purchasing a new vehicle is represented in the model as a discrete choice model following a nested Weibull formulation. The upper level of the decision tree includes ICE types, battery-based electric cars and fuel cell cars.



Normal scrapping is represented using a Weibull reliability function with parameters calibrated by country. The model also includes dependence of parameter values on income expectation.

The annual mileage of vehicles depends on both type and age, as the economic cost of using a vehicle increases with age. As a consequence, the lower usage rates of yet not scrapped old vehicles is endogenous in the model – this is a major change compared to the previous version of the vehicle stock module.

Premature scrapping of a vehicle is endogenous and occurs when fixed and variable operating costs are higher than total costs (including annuity payment for capital) of a new vehicle. The frequency of premature scrapping is represented by a logistic function.

The EURO standards on pollutant emission performance are explicitly represented in the model for all types of vehicles, while the standards on specific CO_2 emissions are modelled as constraints applying on *average* emission performance over all new vehicles that are available for choice- if the average CO_2 label is higher than the applicable standard, the model applies a cost penalty on the purchasing costs of each vehicle type proportionally to the difference between the vehicle's label and the standard, leading to changes in the purchasing choices.