Stock-driven scenarios on global material demand: the story of a lifetime

Deetman, S.P.

7.

A baseline scenario for material use in vehicles

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This chapter has not been published, but is added to provide perspective and is used in the synthesis, Chapter 8.

Abstract

In order to estimate the future contribution of vehicles to global material use, we present a model that translates a given demand for freight and passenger transport into the in-use vehicle stocks, both in terms of number of vehicles as well as their weight and material composition. Subsequently, we apply vehicle lifetimes in combination cohort-specific dynamic stock modelling to come up with the corresponding annual material flows related to vehicle production and decommissioning. We use the IMAGE model elaboration of the second Shared Socio-economic Pathway scenario to present the baseline developments of global vehicle-related material stocks and flows, without assuming additional climate action or material efficiency strategies.

Results show that, given current trends, global vehicle stocks as well as their corresponding annual demand for materials are likely to roughly double between now and the year 2050, mostly as a consequence of passenger car use. The inflow of materials required for vehicle production will continue to be larger than the corresponding outflow of decommissioned vehicles, thus presenting a challenge for achieving fully circular material flows in the transport sector, both with regards to bulk materials in vehicle bodies as well as for critical raw materials used in batteries for electric cars, buses and trucks. However, we also identify some regions for which in-use stocks of specific vehicles will shift from being a net sink to a source of materials, as a consequence of stabilizing population and saturating vehicle stocks. The presented model can thus be used to dynamically assess the global role of materials in vehicles and could complement existing transport models to better capture the synergies and trade-offs of climate and resource-oriented policies.

7.1 Introduction

The demand for transportation, be it of passengers or freight, causes about a quarter of global greenhouse gas emissions (Zhang and Fujimori 2020). Efforts to reduce the climate impacts of transport activities are currently being developed and deployed worldwide (Creutzig 2016; Zhang and Fujimori 2020). While the focus of many of these efforts has been primarily on the energy use through improvement of energy efficiency (Keith et al. 2019; Yeh et al. 2017), the use of alternative fuels (Edelenbosch et al. 2017) or new drivetrains in vehicles (Gómez Vilchez and Jochem 2020; Lombardi et al. 2020), some studies have drawn attention to possible trade-offs with respect to vehicle material use (Busch et al. 2014; Deetman et al. 2018; de Koning et al. 2018; Watari et al. 2019; Hertwich et al. 2019), and the related environmental impacts (Van der Voet et al. 2019; Watari et al. 2021).

While various studies have focused on the possible role of vehicles in driving the future demand for critical raw materials (Jones et al. 2020; Månberger and Stenqvist 2018), the current importance of bulk material use in vehicles, has previously been addressed using tools like Material Flow Analysis and Economy Wide Material Flow Accounting. Indicating that at the global level, the production of vehicles is responsible for about 13% of annual global steel demand (Cullen et al. 2012; IEA 2020), 8% of annual copper demand (Yoshimura and Matsuno 2018) and about 20-26% of annual aluminium demand (Cullen and Allwood 2013; Jones et al. 2020; Liu et al. 2012).

Such global overview studies, however, often lack the level of detail required to distinguish the role of different transport modes or vehicle technologies in driving the annual material demand. Even though these are essential and dynamic determinants of the development of vehicle related environmental impacts (Kaack et al. 2018; Cuenot et al. 2012; van Vuuren et al. 2017a; Mittal et al. 2017). Some exceptions exist, such as a recent study by the International Resource Panel (Hertwich et al. 2020) and some relevant regional analyses (Wang et al. 2015; Giljum et al. 2016; Liu et al. 2020) or studies addressing only one vehicle type (Habib et al. 2020). These show that the integration of a detailed material perspective in transport models is required in order to get a more comprehensive understanding of the future role of materials in a rapidly changing transport sector worldwide, which would enable the consistent and simultaneous assessment of policy objectives related to both climate change and the circular economy (Pauliuk et al. 2017).

This study aims to take a first step, and adds to the existing knowledge on material use in vehicles by developing a comprehensive model that generates long-term insights in the global material stocks as well as the corresponding material in- & outflows related to all vehicles, both passenger & freight, based on readily available international scenarios from the shared socio-economic pathways (Riahi et al. 2017). The model covers both bulk and critical material use in a range of vehicles and drivetrains, so that results are relevant with respect to material scarcity analysis as well as with respect to identifying the impacts of vehicle production, both now and into the future.

The analysis in this chapter is limited to a so-called baseline in the sense that it does not address fleet changes due to additional climate policy efforts, nor does it implement increasing material efficiencies or circular economy strategies related to vehicles. While the simultaneous assessment of climate and resource oriented policies would ultimately be the purpose of the developed model, we think that a description of the basic assumptions and relevant ongoing developments in the transport sector could contribute to a valuable understanding of the global importance of materials in vehicles.

7.2 Methodology

We use existing IMAGE model output for the Shared Socio-Economic Pathways as a starting point for our analysis and model development, because of their global coverage as well as their consistent narratives with a long term perspective (Riahi et al. 2017). For the purpose of this study, and similar to the approach in other chapters, we choose to work with the SSP2 baseline as it resembles a so called ‘middle of the road’ scenario without dramatic deviations from observed trends in the projections for population, affluence and lifestyles (van Vuuren et al. 2017b). Though it may be possible and worthwhile to explore the implications of other SSP baseline scenarios or their climate policy variants, the purpose of this chapter is to explore and document the basic model on material use in vehicles based on the IMAGE model output. More details regarding the narrative of the SPS2 scenario can be found in Appendix 1.

7.2.2 Number of vehicles and their weight in stock

The IMAGE model provides the global demand of passenger kilometers and tonne-kilometers and their modal split based on a model developed by (Girod et al. 2012); shown in Figure 7.1 are the model outcomes for the SSP2 baseline scenario as elaborated in (van Vuuren et al. 2017b). This demand for transportation is translated into the number of vehicles, by type, that were required to fulfill this service. To do so, we apply average capacity, load factors and mileage per vehicle type as detailed in Table 7.1. The vehicle weights indicated in the same table are subsequently used to derive the total weight of the in-use vehicle fleet, by vehicle type. These weights refer to the vehicle body including wheels and drivetrain, the weight and the composition of batteries used in electric vehicles is accounted separately in Section 7.3.

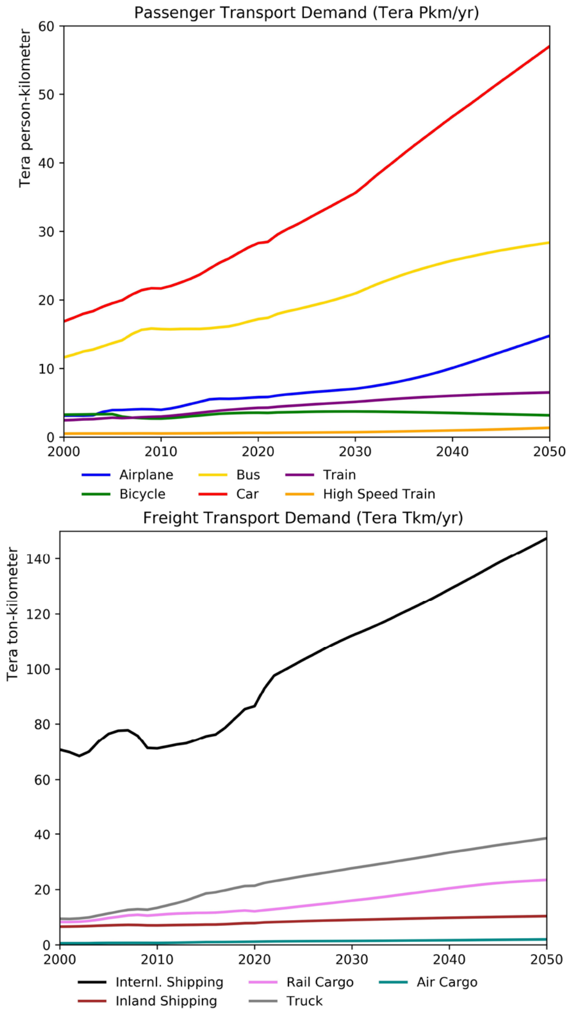

Figure 7.1. *Passenger & Freight Transport Demand in (Tera Pkm or Tkm) in the IMAGE model SSP2 scenario (2020).*

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Table 7.1. *(page 138) Summary of the assumptions on current loads, mileage and body weights of vehicles. *mileage & load factor for cars & buses shown here are an average of the regional mileage applied based on the indicated sources, car weight is an average of different drivetrain types applied based on* (Hawkins et al. 2013)*, so (plugin-) electric vehicles have heavier bodies.** While the load factor for trucks is set to 100% because the indicated capacity represents average load, given by* (IEA 2017)*, the load factor for passenger trains is assumed to be 100% as a global average between relatively low occupancy rates typically reported in European studies and high occupancy rates in regions like India and China as reported by* (IEA 2019)*. *** The indicated capacities for international shipping are for 2018, the model applies dynamic assumptions between 2005-2018 based on* (Equasis; UNCTAD 2005)*.*

Passenger Vehicle	Type	Mileage (km/yr)	capacity (persons)	Load factor (%)	Empty weight (kg)	sources
Airplane		2,133,500	206	82%	60,558	(Airliners.net 2020; Airbus 2020, 2019; Boeing 2020b)
Train	Regular	138,500	400	100%**	252,000	(Connor 2011; Railfaneurope.net 2020; NS 2020; Messmer and Frischknecht 2016a; Spielmann et al. 2007; IEA 2019)
	High Speed	393,300	472	69%	424,000	(UNECE 2017; Doomernik 2015)
Bus	Regular	51,000*	57	43%	14855	(Huo et al. 2012; Schoemaker 2007; Ford 2019a; IVECO 2010; Mercedes-Benz 2020, 2018; ISUZU 2020; BYD 2019; Energy 2018; ABA Foundation 2016; Federal Highway Administration 2010; Kuhnimhof et al. 2017; CBS 2019; Statistics Norway 2020; Hill et al. 2015; Goel et al. 2015; Domingo et al. 2015; Oanh and Van 2015; UITP 2017; Adra et al. 2004; U S Department of Transportation 2019; Özdemir et al. 2015; Zheng et al. 2014; Liu et al. 2019; Yan and Crookes 2009; Singh et al. 2017; ADB 2018; Federal Highway Administration 2020)
	Midi	57,300*	23		7324	
Bicycle		2,400	1	100%	17.2	(Chang et al. 2012; Bonilla-Alicea et al. 2020; Leuenberger and Frischknecht 2010)
Car		14,200*	4	45%*	1500*	(Deetman et al. 2018; Girod et al. 2012; Hawkins et al. 2013)
Freight Vehicle	**Type**	**Mileage (km/yr)**	**capacity (tonnes)**	**Load factor (%)**	**Empty Weight (kg)**	**sources**
Airplane		2,133,504	61	49%	95843	(Casanova et al. 2017; Airliners.net 2020)
Rail		67,484	4,165	45%	1,764,500	(Railway Association of Canada 2018; Messmer and Frischknecht 2016a; Furtado 2013; Dick et al. 2019; IRG-rail 2013; Bureau of Transportation Statistics 2017)
Truck	Light Commercial	13,000	0.74	100%**	1,728	(IEA 2017; Tu et al. 2014; Ligterink 2016)
	Medium	37,000	7.95		8,229	
	Heavy	52,000	14		15,947	
Shipping	Inland	26,677	1,250	71%	322,000	Estimates based on (Bačkalov et al. 2014; Spielmann et al. 2007; Maraš 2008; CCNR 2020)
International shipping	Small	27,000	375***		77,625	(Equasis; UNCTAD 2005; Spielmann et al. 2007; Kristensen 2013)
	Medium		8,215***		1,306,200	
	Large	100,000	53,051***	65%	7,639,300	
	Very Large	145,000	147,805***	50%	19,510,300	

The transport demand is described by the SSP2 baseline scenario, as displayed in Figure 7.1, and is the result of trends in both population and GDP of 26 regions, combined with assumptions on converging travel time budget (TTB) and travel money budget (TMB) as detailed in (Girod et al. 2012). Passenger transport demand, expressed in person kilometers, continues to be dominated by travel by car, while the majority of freight movement, expressed in ton kilometers, is provided through international shipping. The stock of vehicles required to fulfill the given demand on an annual basis is consequently determined using the vehicle specific mileage, capacity and load factor as detailed in Table 7.1.

Some exceptions are made with respect to the calculation of in-use stocks of vehicles for cargo planes, buses, trucks and international ships. The number of cargo planes is halved given that about 45% of air cargo is moved in the surplus cargo space of passenger aircrafts (Boeing 2020a; Airports Council International 2019). While the IMAGE model discerns different vehicle drivetrains, it only distinguishes one bus size and two sizes of trucks (heavy and medium), our analysis expands the coverage of vehicle sizes by adding a smaller midi-bus and a Light Commercial Vehicle (LCV) truck with a Gross Vehicle Weight below 3.5t. We do so, to capture the higher material intensity per ton-kilometer or per person-kilometer for smaller vehicles. Practically, we maintain the total IMAGE transport demand but assign 6% of bus travel to midi-buses based on data in Table 7.1 & (UITP 2019) and we assign 4% of the Tkms by truck to Light Commercial Vehicles, based on (IEA 2017). Finally, we disaggregate the total demand for international shipping to small, medium, large and very large vessels based on sources shown in Table 7.1 and we account for the known development of fleet and ship capacities between 2005 and 2018 based on (Equasis; UNCTAD 2005) as shown in the Appendix 7. Capturing these dynamics in shipping fleet and vessel sizes is important to address the increasing material efficiency of freight transport by increasingly larger ships.

7.2.3 Vehicle fleet validation

Where possible we compare model outcomes to available estimates of current vehicle fleet sizes based on literature as shown in Table 7.2. The basis for comparison here is the total number of vehicles in use. It can be seen that, in general, the model performs better for passenger vehicles than for freight vehicles, when comparing to literature estimates. We'll elaborate on some of the observed model mismatch below.

The model mismatch may be caused by various sources, such as the originally modelled demand for transportation (in pkms/yr or tkms/yr) which is known to be highly uncertain (Yeh et al. 2017), by the assumptions in translating annual demand to the number of vehicles in-use, or by the lack of reliable global statistics on vehicle stocks. While at a first glance, the comparison may seem to suggest considerable model inaccuracies or even systematic underestimation of vehicle stocks, in most of the cases where the model deviates more than 10% from the available literature sources, the high deviation could be explained by the transport demand (in pkm/tkm, see Figure 7.1) as provided by the IMAGE model. For example, the used travel demand by passenger airplanes is exactly 33% lower in 2018 as reported by (IATA 2019) and, similarly, the person kilometers traveled by bus according to the IMAGE model are higher than reported by (ITF 2019), possibly explaining the higher results in terms of vehicle count.

The same holds for most freight vehicles, where the model predicts about 4 times more cargo planes, but this is driven by the IMAGE data, which prescribes about 4 times as much Tkms shipped by air than reported by (IATA 2019). Similarly, the used estimates of Tkm demand by trucks and international ships are about 30% lower than reported in (IEA 2017) and (UNCTAD 2019), thus explaining the majority of the mismatch in the number of vehicles. While this does not mean that the calculated number of vehicles, or the subsequent material calculations, are undisputable, it seems to suggest that generally, there is a large uncertainty when it comes to travel and transport demand at the global level.

While it is currently beyond the scope of the analysis in this chapter to resolve all these uncertainties, we develop a model that accounts for the number of vehicles and their composing materials based on the available information, while acknowledging that further validation and consolidation of global vehicle fleet statistics, both with regard to annual demand, the total number of vehicles, or details regarding average mileage, capacity and load, would be valuable to improve the model. We will elaborate on these and other possible model improvements in the discussion section.

7.2.4 Material in Vehicle Bodies

Given the total number of vehicles and their weight, we derive relevant material fractions based on the vehicle composition shown in Figure 7.2, which was derived from 20 studies, detailed in Table A7.1 in Appendix 7. Here, we consider the materials in the vehicle body, the wheels, as well as the drivetrain. The figure shows a variable material composition with a high fraction of steel in cars as well as in heavy vehicles such as buses, trains, ships and trucks. Aluminium seems to be more commonly used in passenger vehicles than in freight vehicles, with the exception of cargo planes.

Table 7.2. *Validation of current global stock estimates (nr. of vehicles in use). In case multiple sources are used, the year of comparison is an average. * For some vehicles, the comparison is based only on selected regions (here, the numbers do not indicate global totals), e.g. inland shipping is compared only for the sum of Europe, China, the US and Russia. In addition, an overview of regional data and other assumptions regarding trains is given in Appendix 7.*

Passenger Vehicle	**Year of compa-rison**	**Current model (SSP2 new)**	**Literature estimates**	**model devia-tion**	**Literature Sources**
Airplanes	2017	15,481	23,000	-33%	(Airbus 2019; Mazareanu 2019; Morris 2017; Boeing 2018)
Trains*	2017	50,870	54,852	-7%	(IEA 2019; Railway Association of Canada 2018; National Bureau of Statistics of China 2021; Lawrence et al. 2019; Bureau of Transportation Statistics 2019; National Transit Database 2019; Rail Freight Forward 2020; Eurostat 2020; Deutsche Bahn 2019; NS 2018; Trenitalia 2018; Department for Transport 2018; JR East 2017; UIC 2018)
High Speed Trains	2019	4,697	4,959	-5%	(UIC 2020)
Buses	2016	12,000,000	10,400,000	15%	(SCI Verkehr 2017)
Bicycles	2014	1.37 Billion	1 to 2 Billion	-9%	Estimate based on (Sibilski 2016) sales in (Mason et al. 2015)
Cars	2016	1.02 Billion	1.1 Billion	-7%	Adjusted from (Yeh et al. 2017; Li and Chen 2019)
Freight Vehicle	**Year of compa-rison**	**Current model (SSP2 new)**	**Literature estimates**	**model devia-tion**	**Literature Sources**
Airplanes	2017	8,051	1,920	319%	(Airbus 2019; Mazareanu 2019; Morris 2017; Boeing 2018)
Trains*	2016	74,560	83,566	-11%	(IEA 2019; Railway Association of Canada 2018; National Bureau of Statistics of China 2021; Lawrence et al. 2019; Bureau of Transportation Statistics 2019; National Transit Database 2019; Rail Freight Forward 2020; Eurostat 2020; Deutsche Bahn 2019; NS 2018; Trenitalia 2018; Department for Transport 2018; Murray 2014; EBRD 2016)
Trucks	2015	108,000,000	186,000,000	-42%	(IEA 2017)
Internatio-nal ships	2018	52,900	76,000	-30%	(Equasis 2019; IHS Maritime & Trade 2019)
Inland ships*	2015	147,400	222,000	-34%	(Rail Freight Forward 2020; Wong 2019; Buzby 2018; Klyavin 2010)

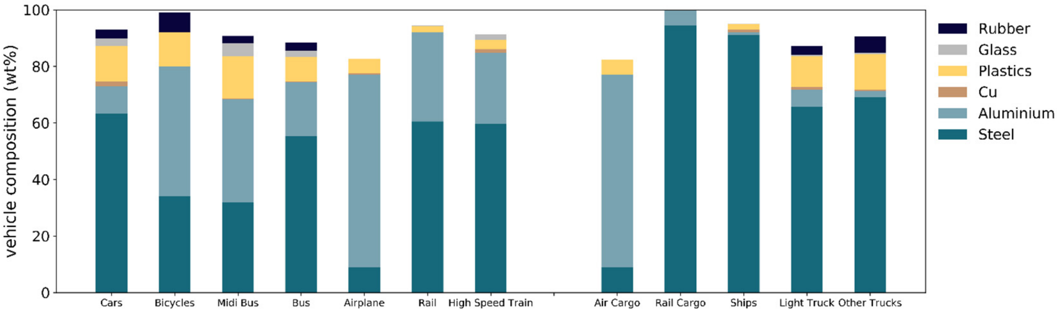

Figure 7.2. *Vehicle material composition (wt%). Average values as applied in the calculations, based on a literature review (see Table A7.1 for details).*

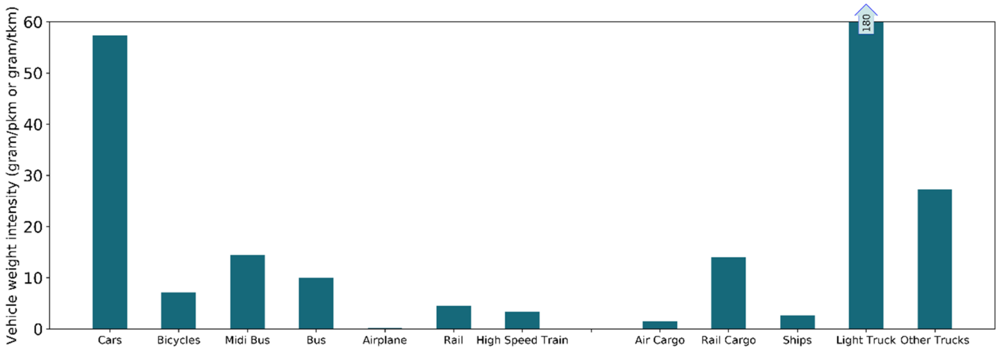

Figure 7.3. *Weight of the current in-use stock, by vehicle, required to provide 1 ton-km or 1 person-km on a yearly basis. The data represents an aggregate indicator of the total weight of vehicles in-use (stock) over the total person-kilometers (for passenger transport) or ton-kilometers (for freight) provided in a year (2018 is used as a basis).*

Figure 7.3 shows the variation in material requirements by vehicle type in order to fulfill the same transport service, either for passenger travel (pkms) or movement of freight (tkms). It shows that travel by car is rather material intensive, while bicycles, trains and especially airplanes require relatively small amounts of materials per pkm to operate. The latter is not surprising, given that airplanes need to fly, but it does not mean that air travel is environmentally friendly, just that airplanes are lighter. However, an overview like presented in Figure 7.3 can be used to identify possible trade-offs between climate-oriented transport policies and material demand. For example, switching from air travel to any other vehicle may have an overall benefit on emissions and the environment (Dobruszkes 2011), but it would present an often overlooked trade off in terms of material efficiency. Alternatively, stimulating a switch from car ownership to more cycling will not only address the impacts of fuel combustion, but also lead to a lower demand for materials.

In freight transport, the range of in-use vehicle stocks per tkm delivered on a yearly basis is lowest for ships and air cargo, but the vehicle weight intensity of light commercial trucks is a factor 5 higher than any other freight vehicle. While this is mostly a consequence of the used assumptions on cargo capacity and annual mileage (Table 7.1) this indicates that even if trucks become fully emission free (e.g. electrified), additional environmental benefits could be attained from optimized logistics and ride planning.

7.2.5 Materials in vehicle batteries

7.2.5.1 Battery weights

The IMAGE SSP2 scenario elaboration assumes the use of batteries in (partially) electric cars, buses and trucks. Given that the number and the share of (plugin/hybrid) electric vehicles is known, we apply a given battery weight per vehicle to derive the total use of batteries in vehicles over time. The default assumptions with regard to battery weight are shown in Table 7.3 below.

Combining the vehicle stock (in number of vehicles) detailed in section 7.1.2 with the weight of batteries in different vehicle types as shown in Table 7.3 gives the total weight of batteries in use. The following sections will elaborate how this was further used to derive the related material use.

Table 7.3. *Battery weight by vehicle (in kg). These represent the assumptions on current battery weights. Battery weights for Hybrid Electric trucks & buses are highlighted with an *, and are derived using a PHEV to HEV ratio based on passenger cars.*

Vehicle	**Variant**	**HEV**	**PHEV**	**BEV**	**Trolley**	**Sources**
Bus	**Regular**	96.9*	194	1256	118	(Ebusco 2020; US Department of Transportation 2017; Gallo et al. 2014)
	Midi	38*	76	546	-	(Gallo et al. 2014; Gao et al. 2017; Volvo 2020)
Truck	**Light Commercial**	27.6*	55.2	254	-	(Pelletier et al. 2014; California Air Resources Board 2015; Gnann et al. 2013; Ford 2019b)
	Medium	41.9*	84	540	-	(den Boer et al. 2013; Ippoliti and Tomić 2019)
	Heavy	69.1*	138.4	901.6	-	(Pelletier et al. 2014; Scania 2020; DAF 2020; den Boer et al. 2013; Gallo 2016; Bisschop et al. 2019; National Research Council 2012)
Car	**Electric**	20.8	44.8	240	-	(Deetman et al. 2021; Nelson et al. 2019)

7.2.5.2 Battery markets & materials

Given the beforementioned assumptions on the total weight of batteries we used additional assumptions on the share of the weight (wt%) of batteries used in new vehicles to find the total weight by battery type. To do so, we combined historic data on mobile battery market shares from (Li et al. 2018) with a moving average of cost-based scenario outcomes from (Deetman et al. 2021), leading to a market development as shown in Figure 7.4a. This market share is input to the material model and battery markets are assumed to be a homogeneous global market, so it is applied to all regions in the material calculations. The relatively large role of Nickel Metal-Hydride batteries in early years is due to their application predominantly in HEVs and PHEVs as well as their relatively low energy density.

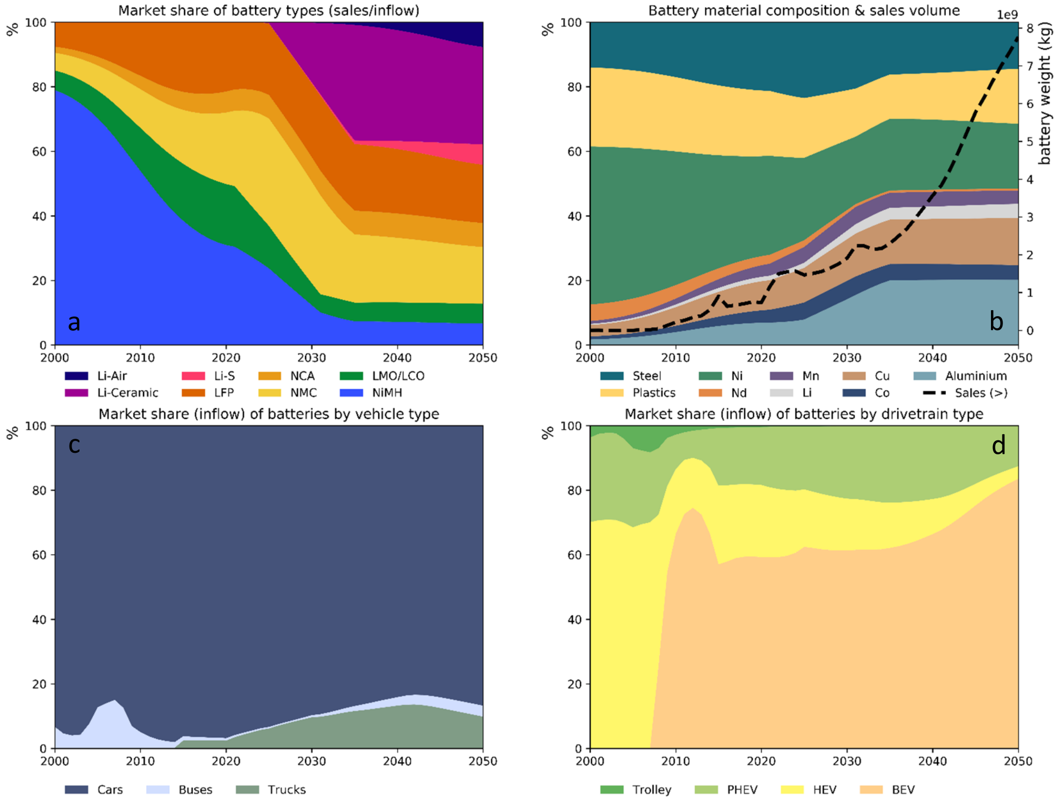

Figure 7.4a-d. *Assumptions on EV Battery markets, by battery type, material composition, vehicle, drivetrain & demand for newly purchased electric vehicles. The market share and material composition in panel a&b are based on a price-driven market model for mobile battery technologies as described in* (Deetman et al. 2021) *in combination with data from* (Li et al. 2018). *This market share is applied globally, thus assuming a global battery market.*

The total battery deployment, the battery market shares together with the material composition of each battery type based on (Deetman et al. 2021) leads to a particular share of the materials used in new batteries as shown in Figure 7.4b. Figure 7.4c-d shows the importance of different vehicles and drivetrains to the global sales, indicating that battery electric passenger cars will dominate global markets in the years to come.

7.2.4 Vehicle lifetimes and dynamic stock modelling

Given the size of the vehicle stock, we applied a dynamic stock model as described by (Pauliuk and Heeren 2018) and available from (Pauliuk and Heeren 2019). This methodology is used to derive the annual vehicle inflow (sales) as well as the size of the annual outflow (decommissioning), corresponding to the stock as detailed in Section 7.2.2. Assumptions on vehicle lifetimes and their lifetime distributions are described in Table 7.4. Next to the mean vehicle lifetime assumptions, Table 7.4 also details the assumptions on the lifetime distributions and the first year of operation. The latter is needed, because we apply a stock-driven dynamic stock model, so it is important to detail the assumptions of the historic development of vehicle stocks before the initial year of the IMAGE scenarios (being 1971), because they affect the calculated inflow & outflow throughout the scenario period.

7.3 Results

The results, both in terms of total global stock and the corresponding annual material demand & scrap flows, are shown in Figure 7.5a-d. It shows that passenger cars are by far the most notable contributors to material stocks, representing about 56% of a total of roughly 5 Gt of material stocks in vehicles worldwide. Not surprisingly, steel is the most important material composing all vehicles, and while material composition of vehicles is assumed to be constant under default model setting, Figure 7.5b shows a slight increase in the relative importance of copper in the stock of vehicles towards 2050 as a consequence of a shift from internal combustion cars to battery electric cars as well as a shift from regular trains to high-speed-trains, both of which use a higher amount of copper than their 'traditional' alternative (See Table A7.1). Figure 7.5c-d also show that the relative importance of different vehicle types in global material stocks depends on the material of interest. Where trucks and ships use relatively little aluminium in comparison to steel, the use of aluminium in buses, trains and even bicycles shows up as more pronounced.

With respect to material flows related to vehicles (dashed lines), the model predicts the annual demand of steel going into vehicle production to grow from about 158 Mt/yr now to about 294 Mt/yr by 2050.

Table 7.4. *Lifetime assumptions. * Standard deviation is expressed as a fraction of the mean lifetime. ** The standard deviation for vehicles other than Light trucks, buses and airplanes is assumed to be the average of these three categories. *** For passenger cars we applied a Weibull lifetime distribution with a shape parameter of 2.01 and a scale parameter of 16.02. **** The first year of operation of cars and bicycles is not necessarily historically accurate, but an assumption in the analysis.*

Vehicle	Type	Mean lifetime (yrs)	Standard dev.*	1st year of operation	Sources for lifetimes (and 1st year of operation)
Airplanes	Passenger	20	0.281	1940	(IATA 2016; Howe et al. 2013; Lopes 2010; IATA 2018) (Capoccitti et al. 2010)
	Freight	21			
Buses	Regular	13	0.322	1895	(Nordelöf et al. 2019; Law et al. 2011; Laver et al. 2007) (Daimler 2008)
	Midi				
Trucks	Light Commercial	14	0.196	1896	(Yang et al. 2018; Law et al. 2011; Sen et al. 2017; Dun et al. 2015) (Daimler 2006)
	Medium & Heavy	8	0.266**		
Trains	Passenger	35		1825	(Stripple and Uppenberg 2010; Nahlik et al. 2015; Yue et al. 2015) (Fava-Verde 2018)
	Freight	38			
	High Speed (pass.)	30		1971	
Ships	Maritime	26		1807	(Dinu and Ilie 2015; Chatzinikolaou and Ventikos 2015; Messmer and Frischknecht 2016b; Fan et al. 2018) (Woods 2009)
	Inland	40			
Bicycle	standard	10		1900****	(Bonilla-Alicea et al. 2020; Luo et al. 2019)
Cars	Passenger	14	***		(Deetman et al. 2018) as in Chapter 3

For aluminium the annual inflow grows from about 21 Mt/yr now to about 44 Mt/yr by the end of the scenario period. These outcomes for historic material demand are at least roughly in line with the studies referred to in the introduction (128 Mt/yr of steel in 2007, compared to 139 Mt/yr according to (Cullen et al. 2012), and 16.5 Mt/yr of aluminium, compared to 12 Mt/yr according to (Cullen and Allwood 2013)).

In addition, Figure 7.5 shows a continuing mismatch between inflow of material into vehicle stocks and the delayed outflow of materials from those in-use vehicle fleets. While this seems to suggest that for both aluminium and steel, even perfect vehicle recycling would only generate enough material to provide roughly 77% of the material demand for new vehicles, this finding is highly dependent on the regional developments. In some regions the demand for transport through specific vehicle types such as buses reaches saturation as an effect of both population dynamics as well as modal shift. This has consequences on whether the in-use vehicle stocks act as a net source or sink for materials in different world regions as can be seen in Figure 7.6.

While Figure 7.6 is based on only a selection of passenger vehicles, thus only representing a small fraction of the total steel flows related to vehicles, it shows that by the end of the scenario period in specific regions, such as China and Japan, the in-use stocks of some vehicles are starting to become a net source of steel, meaning that the annual outflow exceeds the required annual inflow. These dynamics are dependent on development of population, GDP and modal shifts, but they indicate a fundamental shift in resource flows at stock saturation, which we can only start to observe within the scenario period, but may become more common after 2050. At the global level, the vehicle fleet will continue to absorb a large volume of materials, but this signal provides a perspective for urban mining and a more circular economy in some regions beyond the scenario period.

With respect to batteries in electric vehicles, however, this shift to a net material outflow is not yet observed before 2050, as can be seen from Figure 7.7. Even in regions with stabilizing population such as China and Japan, the continued growth of per capita GDP leads to a continuing rise in the demand for cars, with a simultaneously increasing role for battery electric vehicles. This is the reason that the batteries in newly purchased (hybrid, plugin and fully) electric vehicles will increasingly outweigh the outflow of end-of-life batteries from decommissioned vehicles. Thus, presenting an increasing challenge in closing the material cycles from vehicle batteries before 2050. Figure 7.7 also shows that the penetration of electric transport is slower in developing regions as a consequence of high initial investment prices for (partially) electric vehicles.

In contrast to findings for other vehicles as shown in Figure 7.6, this leads the ‘Steady Developed’ regions such as (a.o) the US and Europe to dominate the annual demand of materials used in electric vehicle batteries (see Figure 7.4b for the individual materials), according to the SSP2 baseline scenario used.

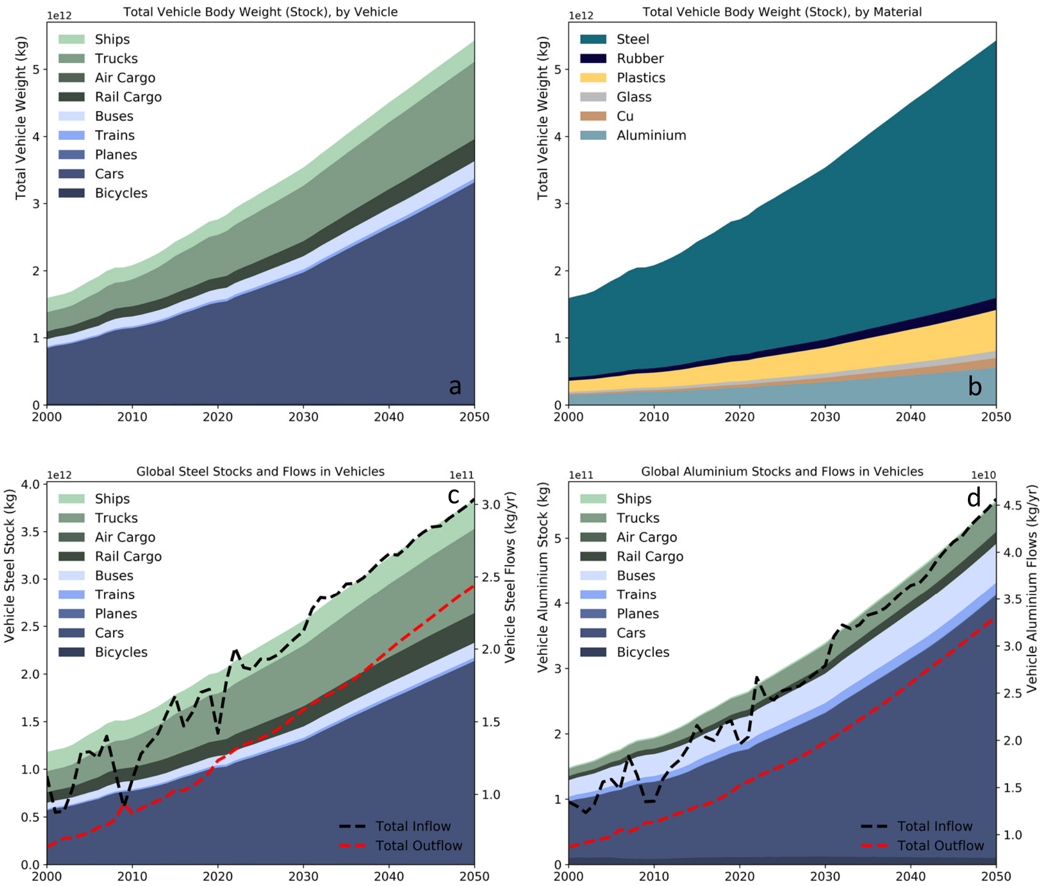

Figure 7.5a-d. *Global Material Stocks and Flows in Vehicles. Top panels show the weight of the stocks, either by vehicle type (a) or by material (b). Lower panels show the size of the stocks and in/out flows for steel (c) and aluminium (d).*

7.4 Discussion & conclusions

The model and the analysis presented in this chapter deal with the expected development of material use in vehicles towards 2050, under baseline assumptions. We used available projections of transport demand from the IMAGE model elaboration of the SSP2 scenario to come up with an estimate of materials in several passenger- and freight vehicles over time. A translation from annual transport demand expressed in person-kilometers or ton-kilometers to the total number of vehicles was made using indicators on vehicle mileage, capacity and load factor, while the material use was determined using vehicle specific weight and composition data, all based on an extensive review of available literature. This approach thus accounts for the heavier vehicle bodies of electric cars compared to combustion-based cars.

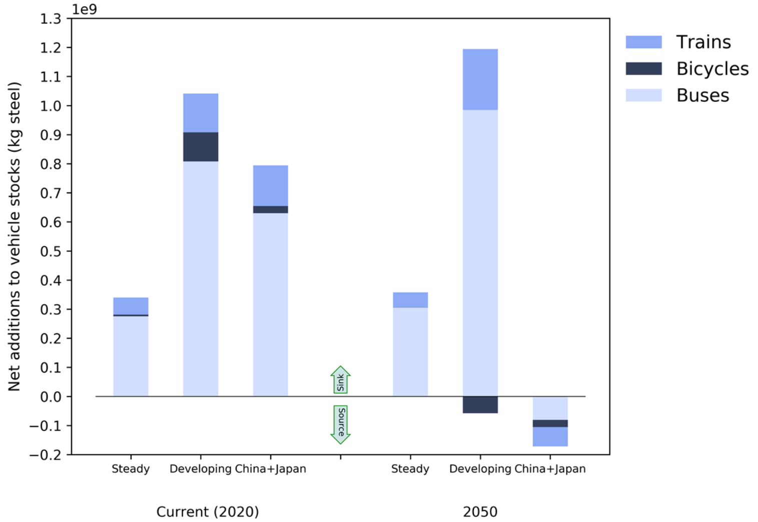

Figure 7.6. *Net additions to stocks of buses, trains & bicycles, as a source or a sink of steel in three global regions. The regional aggregation used assigns the following regions as 'Steady' (based on population growth projections): North-America, Europe, Ukraine, Russia, Middle East & Australia. 'Developing' regions have a higher population growth and are defined as the remaining regions minus China and Japan.*

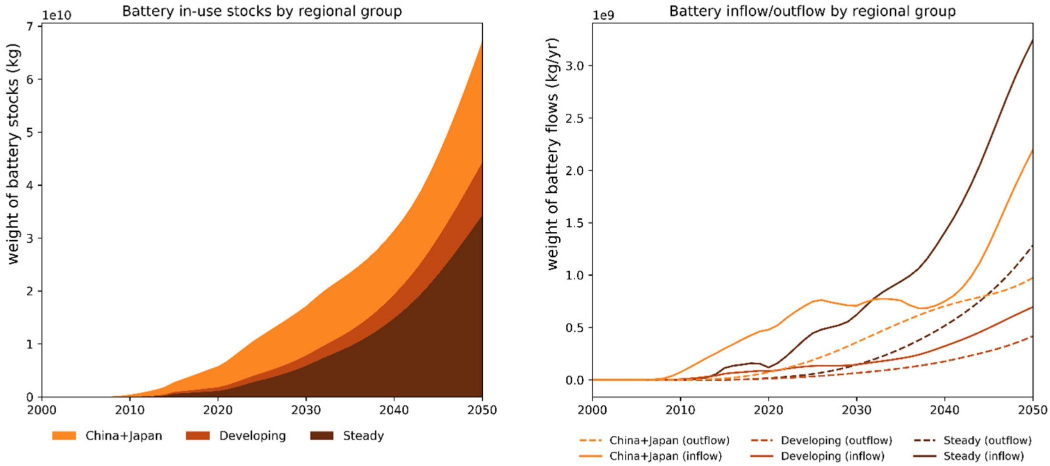

Figure 7.7. *Total weight of the battery stock, inflow and outflow by aggregated world regions. Regional aggregation is the same as detailed with Figure 7.6.*

The results show that a continued growth in transport demand will lead to a substantial expansion of in-use vehicle stocks, leading to roughly a doubling of the stock weight to more than 5 Gt as well as a doubling of the annual demand of materials used in vehicle production. Cars continue to dominate the total weight of the in-use vehicle stock, with steel being the most important material by weight. While vehicles other than cars are sometimes omitted in studies on material stocks, we show that they compose a relevant fraction of the total vehicle weight, at about 44 wt% of the modelled stock.

Given that stocks are growing and that the lifetime of most vehicles exceeds 10yr we observe a lag between the demand for materials in vehicle production and the availability of secondary raw materials from scrapped vehicles at the global level. This mismatch is also observed in battery electric vehicles and highlights a fundamental challenge to reaching a fully circular flow of both bulk and critical raw materials any time before 2050. Some exceptions exist, however, for example for buses, bicycles and trains in regions where stock saturation is observed as a consequence of stabilizing or declining population size and simultaneous modal shift, such as China and Japan. Here, targeted waste management may be required to make optimal use of vehicle stocks that will likely turn from a net sink into a source of materials before the year 2050. In general, we expect such shifts, where vehicle in-use stocks become a net source of recyclable materials, to happen more often beyond 2050.

We present our analysis as an initial attempt to provide a complementary material perspective to the often energy-oriented scenario models on the transport sector, but also highlight some possible model improvements. Starting with the imperfect match between the modelled number of vehicles and values found in general literature; while we find that most of the model deviation could be explained by the used scenario indicators on global transport demand, which are generally highly uncertain, it would be valuable to explore the effect of more realistic assumptions on vehicle mileage, capacity and load factors. Possibly even accounting for their change over time. Secondly, the model presented here does not account for actual recycling rates. Even though recycling rates for materials from vehicles such as cars can be quite high (Andersson et al. 2017), it would be worth to expand the model based on realistic assumptions regarding recycling. Finally, we feel that some perspectives beyond mere 'baseline' assumptions could provide more policy relevant insights with respect to the role of climate policies or material efficiency strategies in curbing the environmental impacts of vehicles and the transport sector as a whole. This could entail the assessment of an entirely different transport demand scenario, or the inclusion of dynamic assumptions regarding load factors, weights and material composition, for example.

Irrespective of these suggested improvements, we feel that the current model provides some valuable insights. First of all, it allows us to assess the future role of vehicles in the global material demand, with details on the contribution of regions, vehicle types, batteries and drivetrains. Secondly, it identified the role of particular in-use vehicle stocks as a potential source for materials towards 2050, this realization can help define synergistic resource policies. Finally, when combined with climate or energy models, our model could be used to highlighting often-overlooked trade-offs between climate & material efficiency policies. Given the increasing efforts to decarbonize the global transport system, the materials required for vehicle production will likely play an increasing role in the remaining environmental impacts related to transportation towards 2050. We hope that the model presented here could provide a platform to account for climate and resource impacts simultaneously.

Acknowledgements

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Appendix

Appendix 7 provides more details with regard to vehicles material composition. Additional details, including future model corrections and updates will be reported in the online model repository available via www.github.com/spdeetman/VEMA.