Environmental Modeling & Assessment (2021) 26:891–909
https://doi.org/10.1007/s10666-021-09760-y

Coupling a Detailed Transport Model to the Integrated Assessment Model REMIND

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Received: 24 February 2020 / Accepted: 15 February 2021 / Published online: 30 March 2021

Abstract
The transport sector is a crucial bottleneck in the decarbonization challenge. To study the sector's decarbonization potential in the wider systems perspective, we couple a large-scale integrated assessment model, Regionalized Model of INvestments and Development (REMIND), to a detailed transport model, Energy Demand Generator-Transport (EDGE-T). This approach allows the analysis of mobility futures in the context of long-term and global energy sector transformations, at a high level of modal and technological granularity and internal consistency. The runtime of the coupled system increases by ~ 15–20% compared with a REMIND standalone application, and first convergence tests are promising. To illustrate the capabilities of our modeling approach, we focus on a reference pathway for Europe. Preliminary results indicate that transport service demands grow in the next decades for both passenger and freight transport. Transport system emissions are expected to decrease in the same time range, due to a shift towards electric drivetrains, advanced vehicles, more efficient modes as well as a slight increase in the share of biofuels.

Keywords Integrated Assessment Model · Transport model · Models coupling · Alternative vehicles

Abbreviations

BEV	Battery Electric Vehicle
CES	Constant Elasticity of Substitution
EDGE-T	Energy Demand GEnerator-Transport
FCEV	Fuel Cell Electric Vehicle
GCAM	Global Change Assessment Model
HSR	High-speed Rail
IAM	Integrated Assessment Model
ICE	Internal Combustion Engine
LDV	Light Duty Vehicle
NG	Natural Gas
REMIND	Regionalized Model of INvestments and Development

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1 Introduction

Mobility is a key energy service for economic development [1]. The transport sector is quite energy intensive, accounting for 28% of total global final energy demand and 23% of global energy-related CO_2 emissions [2]. The sector largely relies on fossil fuels: in 2014, 95% of the sector's energy consumption consisted of oil products [3]. With the aim of halting global warming and transitioning to CO_2 neutrality in the coming decades, the sector should undergo a deep transformation [4]. Transport is, however, considered a crucial bottleneck of the transition towards carbon neutrality [5, 6, 7]. Models have been used in the past in an attempt to capture the sector dynamics and analyze decarbonization strategies of the transport system, and a variety of transport-focused models have been developed. Transport sector models tend to either (1) be structured as very detailed technology-rich sectoral models that only marginally account for larger system transformations, or (2) be part of aggregated energy system models with key feedbacks across economic sectors but limited detail on the specific technologies (see, e.g., [8]). Transport models in IAMs usually suffer from the shortcomings of (2) and provide highly aggregated demand sector proxies in aggregate macroeconomic environments,

Table 1 REMIND and EDGE-T main characteristics

	REMIND	EDGE-T
Model type	Energy-Economy-Climate model	Transport Energy Model
Sectors represented	Buildings, industry, transport, power sector	Transport
Spatial resolution	Global model, regional resolution	Global model, country-level resolution
Sectoral resolution	Aggregate sectoral representation	Detailed representation of transport system
Year first release	2020 (open version. The REMIND-R model was first published in 2010 [19])	2020
Hardware required	16-GB RAM or higher, Core i7CPU	Tested on a laptop with 16-GB RAM and Core i7CPU
System required	Operating system: Windows, Linux, MacOS Software: GAMS (solver: CONOPT 4) R Latex R packages: PIK-PIAM libraries https://github.com/pik-piam	Operating system: Windows, Linux, MacOS Software: R R packages: PIK-PIAM libraries https://github.com/pik-piam
Availability	https://github.com/remindmodel	https://github.com/pik-piam/edgeTransport

as their level of detail on the demand representation is usually limited by computational restrictions. IAMs are traditionally more focused on the supply side (see, e.g., [9]), but an increasing interest in demand oriented policy analysis [10–13] calls for improvements also in the demand representation.

The advantages of integrating models to increase sectoral detail but limiting complexity are also underlined in [14]. There have been previous efforts to overcome this limitation. The system engineering energy-economy model TIMES/MARKAL of the USA has been coupled to a bottom-up, technology-rich model for transportation [15]. In [16], a hybrid model with top-down and bottom-up characteristics was applied to analyze consumers' preferences in the industrial, residential, and transportation sectors. The authors of [17] overcome the limited representation of perfectly informed consumers in an economic simulation model by integrating a road transport sub-component. In [18], the authors emphasize the importance of a careful calibration of the coupled system comprising a multi-sector multi-region model and a technology-rich transport model.

We contribute to this research area by coupling the global-scale, multi-region energy economy-climate model Regionalized Model of INvestments and Development (REMIND) to a detailed model of the transport sector, the "Energy Demand Generator Model for the Transport Sector" (EDGE-T in the remainder of this article). This system allows a consistent representation of final energy supply, modal and technology choice, and transport service demand, focusing on the feedbacks between the competition for scarce resources at a macroeconomic level and detailed transport modeling and preferences. The purpose of EDGE-T is further to provide a detailed and easily extendable environment to evaluate transport-specific policies. REMIND on the other hand provides a coherent framework of the full energy-economy system, which ensures the consistency of transportation demand with economic drivers, the energy supply system, and competing demands from other energy end uses. Coupling the two models allows both the assessment of the feedbacks between the transport system and the economy, and consistent evaluation of the impact of detailed transport policy scenarios within a complete macroeconomic framework. The implementation of EDGE-T in this configuration can still be used as a flexible standalone environment for transport-specific assessments with limited computational burden. Both models are available on GitHub (see "Availability" in Table 1). The models and their main characteristics are schematically reported in Table 1 and described in detail in Sects. 2 and 3. Section 4 describes the coupling between the two models. In Sects. 5–6 we report the results, with a focus on Europe, and in Sect. 7 we synthesize the main conclusions of this study.

2 Description of the Modeling Tools: REMIND

REMIND is a global energy-economy-climate model [20, 21]. The model incorporates the economic and climate systems, with a fairly detailed representation of the energy sector. The model time frame spans from 2005 to 2100 and represents the world divided into a set of aggregated regional entities. The spatial aggregation adopted for this study is reported in the Appendix (A1) and comprises 12 regions. For each region, the model maximizes utility generated by labor, capital, and energy use by means of a nested constant elasticity of substitution (CES) function [22]. The CES stages the competition between alternative production

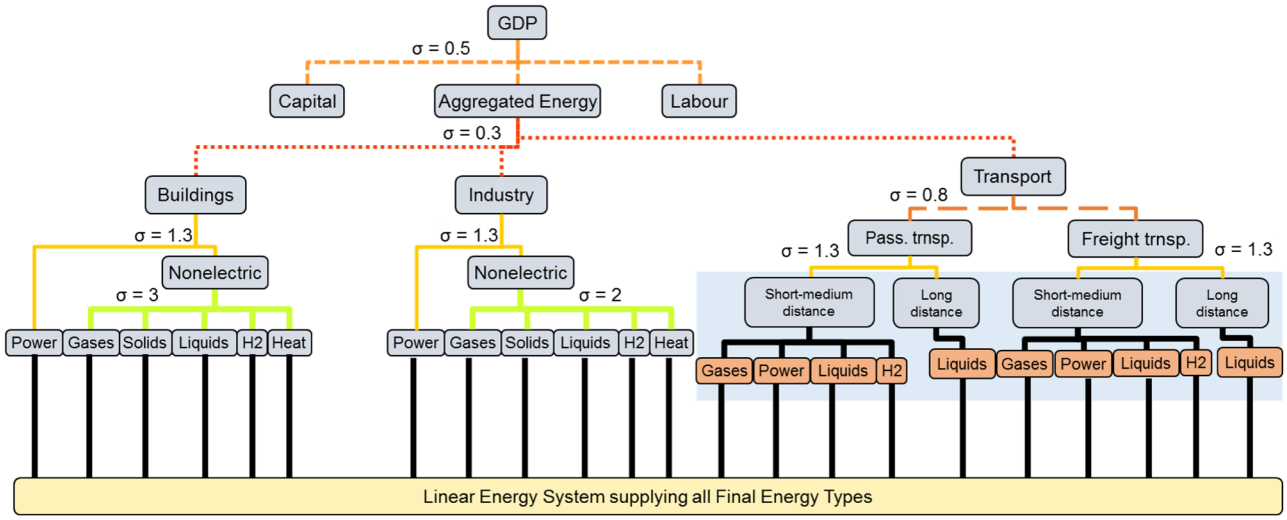

Fig. 1 REMIND CES structure. Energy carriers are provided by the Energy System Module (ESM) to the CES lowest-level nodes. Three energy-demanding sectors, Buildings, Industry, and Transport, are explicitly represented in the model. The area of the CES interacting with EDGE-T is highlighted in the blue box

factors and accounts for the utility value associated. The substitutability between factors is expressed via elasticity parameters σ, which define the demand response to a variation in prices. Low elasticity ($\sigma \to 0$) represents a competition between production factors that are hardly substitutable, and therefore will tend to be used in fixed proportions, whereas high elasticity ($\sigma > 1$) refers to production factors that are good substitutes.

For the purpose of this study, we modified the pre-existent representation of the transport branch in REMIND [23]. The substitutability between the short/medium and long sub-nodes within the passenger and freight nests is assumed to be slightly higher than 1 ($\sigma = 1.3$) to represent the possible (but limited) interchangeability across short-medium and long-distance travel in an increasingly globalized world. The elasticity between freight and passenger is instead assumed lower than 1 ($\sigma = 0.8$), to represent the difference in nature of transport for goods and passengers. While one might argue that the fundamental difference between freight and passenger transport should lead to no substitutability at all between the two nodes, a certain substitutability is required to allow both nodes to react independently to price signals—e.g., if cheap decarbonization options exist for passenger but not freight transport, one would expect to see a stronger reaction to high carbon prices in the demand for freight transport compared with the demand for passenger transport. If one would use very low elasticities close to 0 between the two nodes, both demands would be depressed similarly.

In a policy scenario, changes in relative energy prices, e.g., due to carbon prices that make carbon-intensive energies more expensive, modify the initial demand configuration, leading the model to favor specific production factors at the expense of others (e.g., towards more efficient energy forms, like electrification). A representation of the CES structure in the coupled version of REMIND is provided in Fig. 1.

In the CES, the energy node comprises the most energy-intensive economic sectors: buildings, industry, and transportation. The three energy demand sectors compete for energy use, and are substitutable with low elasticity.

The transport branch of the CES has been modified for consistency with the EDGE-T model presented in this study.[1] Transport is divided into passenger and freight demand, which each include a short-to-medium and a long-distance option. Transport CES nodes represent energy service demands (units: ton kilometers for freight, passenger kilometers for passenger transport), as the benefit to households and firms comes from the amount of traveling and transported goods. The initial configuration of demand for each production factor is provided exogenously in the model calibration phase, where the set of CES efficiency parameters is calculated for the baseline economic and technological development scenario. The unit conversions along the CES tree are included in the efficiency parameters. The representation of the transport sector in the standalone version of REMIND is limited by two important constraints. First, given that the model represents the full energy, economy, and climate systems, the level of granularity achievable in the transport sector is limited due to computational constraints. Second, REMIND determines the amount of energy

[1] To compare with the previous structure, the reader is invited to refer to [23].

Table 2 Representation of the Weibull-based nested structure from EDGE-T

Aggregate mode	Sublevel	Vehicle size	Powertrain
Transport passenger[a]	LDV	4 wheelers (mini, subcompact car, compact car, mid-size car, large car, van)	ICE-Liquids[b] ICE-NG ICE-Hybrid[c] BEV Fuel Cell Electric Vehicle (FCEV)
		2 wheelers (small motorcycle, large motorcycle)	ICE-Liquids BEV
	Buses and coaches	-	ICE-Liquids ICE-NG Electricity Hydrogen
	Rail and HSR	-	Liquids Electricity
	Aviation	-	Liquids
Transport freight	Road	Truck (< 3.5) Truck (> 3.5 t and < 16 t) Truck (> 16 t)	ICE-Liquids ICE-NG Electricity Hydrogen
	Rail	-	Liquids Electricity
	Shipping	-	Liquids
International passenger transport	Aviation	-	Liquids
International freight transport	Shipping	-	Liquids

[a]Passenger navigation is not included due to the small share in total travel

[b]Gasoline and diesel are not separately modeled

[c]In the current model version, only mild Hybrid and full Hybrid are implemented

to allocate to the different demand sectors (transport, buildings, industry), depending on the initially provided demand pathways and the marginal utility associated with each extra unit of energy demand, in a decision-making process mainly driven by historic demands and resource scarcity.

The coupling with EDGE-T improves the representation of transport in REMIND. It significantly increases the level of detail on the technological and modal choice. It also adds further criteria to the decision-making process. This enables the representation of market failures and myopic customers, overcoming the idealizations of pure economic optimization. The literature shows that many factors, monetary or not, influence transport choices. Actual decisions result from a combination of tangible costs and other decision drivers: time invested in traveling [24, 25], inertia of the infrastructure system [26], and behavior of consumers [15, 27–30], among others. Technology-related costs and intangible costs are shared differently across modes and vehicle types.

The consistency between REMIND and EDGE-T is achieved via two distinct steps. First, the baseline demand for transport energy services in REMIND's production function is calibrated to the baseline projections from EDGE-T for all regions and time steps. Second, REMIND and EDGE-T are solved iteratively to ensure consistency between the prices and quantities of energy services required by the transport system. In the iterative process, EDGE-T informs REMIND about the market shares gained by the fuel alternatives of a transport node (orange boxes in Fig. 1), as well as the per-unit costs and per-unit energy intensity of each node. On the basis of this information, REMIND determines the volume of energy services demand for transport.

3 Description of the Modeling Tools: EDGE-T

EDGE-T is derived from the Global Change Assessment Model (GCAM) transport module [31, 32] with a high level of detail in its representation of technological and modal options. It is a partial equilibrium model with a nested Weibull-based function [33, 34]. The nested structure is reported in Table 2 for an illustrative case[2]

[2] The structure depends on the available data for the selected country/region: vehicle classes can vary.

EDGE-T achieves a detailed representation of fleet composition in a flexible structure. It covers both passenger and freight transport, further distinguished by domestic and international travel. Investments and capacity additions are accounted for using levelized cost per kilometer (tangible and intangible), with a default depreciation rate of 5%. It includes an explicit representation of vintages for light-duty vehicles (LDV). EDGE-T provides also projections of demand for transportation, based on regression formulations. In a standalone operation, EDGE-T runtime is 1 min on a single core thereby utilizing around 1 GB of RAM.

In order to reflect the competition for scarce resources, fuels, and emissions, a macroeconomic framework is required, represented by a set of inputs: GDP, population, fuel prices, income and price elasticity, and a set of assumptions on technological development. The model has country-level geographic aggregation and spans the time period from 1990 to 2100, with time steps of 5 years initially and 10 years after 2060, and is calibrated to historical data up to 2010.

For European countries, the historical demand is based on the TRACCS database [35] and ACEA [36], as well as on the GCAM model database [32]. For energy efficiency of European LDVs, we base our assumptions on [37], for both historical and projected values. Transport costs and the value of time are based on [32, 38, 39]. For China, we base our assumptions on [40] as well as on the GCAM database [32]. For other regions, we rely solely on historical data from the GCAM database [32]. If necessary,[3] we perform a downscaling from regions to country level using GDP as a weight for extensive variables (e.g., transport demand), while intensive variables (e.g., energy intensity) are kept constant for each of the sub-countries of a given region. GDP and population are usually determined by a "Shared Socioeconomic Pathway" scenario [41]. A learning rate[4] of 20% induces a decrease in purchase costs for battery electric vehicles over time [42]. The income elasticity for passenger modes is based on own calculations derived from [43] and [32]. The data input structure by source is represented in Table 3.

Table 3 Input data of EDGE-T classification

Region	Entry	Source
EU Countries	Historical demand	[32, 35, 36]
	Energy efficiency LDV	[37]
	Energy efficiency (non-LDV)	[32]
Non-EU countries	Historical demand	[32, 40]
	Energy efficiency	[32]
All countries	Costs, value of time	[32, 38, 39]
	GDP, population	[41]
	BEV learning rate	[42]
	Income elasticity	[32, 43]

3.1 Market Share Allocation

Transport is represented as a nested structure of subsequent choices among comparable alternatives. The market shares among alternatives are attributed at each level of the nested structure via a Weibull-based modification of the logit approach [34]. As summarized in [33], this approach is consistent with a wide body of literature that uses logit-type functions in order to represent consumer choices under probabilistic conditions. The utility maximization function of a decision maker facing J choices is assumed to feature an independently, identically, distributed error ε_j associated to each jth choice. If ε_j follows a Gumbel (type I extreme value) distribution, the approach is defined as conditional logit model or multinomial logit model, since the difference between two Gumbel distribution is distributed logistic. In [34], the authors describe a modification of this approach in the context of energy technology choice, employing a Weibull (type III extreme value) distribution for the error in lieu of the Gumbel distribution. The Weibull-based formulation is adopted in the present study.

Given the global scope of the REMIND model, a very rich dataset of historical data about market shares and prices of transport technologies would be required for a solid statistical model estimation. Unfortunately, the data available to the authors shows large differences in quality across world regions. However, given the long-term scope of the REMIND model, the authors consider a statistical analysis being beyond the purpose of this study. The introduction of new players in the transport sector, the economic growth of developing countries, and the increasing importance of climate change mitigation policies could dramatically change the historical patterns, calling into question the reliability of historically determined parameters. To compensate the lack of statistical foundation in the model estimation, a sensitivity analysis of the key parameters is provided.

Each option present in the nested structure gains a market share which depends on its price, in comparison with the associated price of alternative technological options and fuels. Non-price-based preferences of consumers towards specific options are considered as well. The allocation of market share for alternative i occurs by means of the following equation, defined across the available n alternatives, for country c and at time step t:

[3] In the current model version, detailed data have been gathered only for Europe and we analyze results at regional level for non-European regions. The model is conceived on a country level to allow country-specific studies, provided that data is available.

[4] We only consider learning by doing, i.e., existing capacities determine technology costs.

Table 4 Summary of the market allocation exponents in the EDGE-T model: λ represents the exponent in Eq. 1 concerning the decision amongst the categories in the sub-level. The sub-level column represents the nested sub-nodes for any given Level (first column)

Level	Sub-level	λ	Source
LDVs and trucks	Powertrain choice (oil, NG, H2, BEV…)	−4	Own calculation (see Supplementary information, A3)
Buses		−4	
4-Wheelers	Vehicle choice (small car, SUV…)	−2	[32]
Passenger transport	Mode choice (rail, road, shipping, aviation…)	−3	[32]
Freight transport		−2	

$$s_{i,c,t} = \frac{W_{i,c,t}\left(p_{i,c,t}\right)^{\lambda}}{\sum_{k}^{n} W_{k,c,t}\left(p_{k,c,t}\right)^{\lambda}} \tag{1}$$

where $s_{i,c,t}$ is the obtained market share, the exponent λ is an intrinsic parameter common to all technologies in the node, $W_{i,c,t}$ is the preference parameter (weight), and $p_{i,c,t}$ is the price.

A synthetic description of the variables in Eq. 1 follows below.

Exponent: This determines the sensitivity of the market share to the price ratio, i.e., how large the price ratio between alternatives must be in order to produce a change in the related market shares. High values lead to a high sensitivity to price variations. The values of the exponents we adopt are reported in Table 4.

Preference Factor: Preference factors are synthetic parameters that describe country-specific preference towards transport alternatives. Their historical trend is calibrated based on historical data, while their trend in time is exogenously set on the basis of scenario assumptions. This requires assumptions on the evolution of the transport system (e.g., development in the infrastructure, shifts in new technology acceptance, evolution of the consumer preferences, government policies). For instance, the current market for private cars shows a pronounced preference towards conventional vehicles. As a case point, only 3.4% of the total European fleet today falls into the alternative-powered vehicles classification [44], due to a number of rational economic reasons (e.g., higher upfront investment, lack of recharging infrastructure, relatively short range for a full charge) as well as a number of behavioral and societal reasons (e.g., neighborhood effect[5] [45], inertia of consumers, range anxiety). In the model, the various drivers contribute each with a different weight to the economically driven decisions of a household. We translate the consumer preference W into an economic equivalent $\tilde{p}$ by equating the two formulations, i.e.,

$$Wp^{\lambda} = \left(p + \tilde{p}\right)^{\lambda} \tag{2}$$

so that it follows

$$\tilde{p} = p \cdot \left(W^{\frac{1}{\lambda}} - 1\right) \tag{3}$$

This formulation allows us to represent Eq. 1 as

$$s_{i,c,t} = \frac{\left(p_{i,c,t} + \tilde{p}_{i,c,t}\right)^{\lambda}}{\sum_{k}^{n}\left(p_{k,c,t} + \tilde{p}_{k,c,t}\right)^{\lambda}} \tag{4}$$

From Eq. 3, we notice that $W \to 1$ corresponds to a $\tilde{p} \to 0$ (high acceptance leads to low inconvenience costs), and $W \to 0$ corresponds to $\tilde{p} \to \infty$ (low acceptance leads to high inconvenience costs).

Price: Prices are taken as the combination of different components, namely, fuel price, non-fuel price, and value of time, following this formulation:

$$p_{i,c,t} = P^{f}_{i,c,t} + P^{nf}_{i,c,t} + P^{T}_{i,c,t} \tag{5}$$

where $P^{f}_{i,c,t}$ represents the price of fuel per travelled km, $P^{nf}_{i,c,t}$ accounts for all vehicle-related costs[6] (purchase cost, O&M costs, registration taxes and subsidies), and $P^{T}_{i,c,t}$ represents the intangible cost of the time invested in traveling. In EDGE-T, it is directly proportional to the average wage $R^{w}_{c,t}$ and inversely proportional to the transport speed $v_{i,c}$ [32], i.e.,

$$P^{T}_{i,c,t} \propto \frac{R^{w}_{c,t}}{v_{c,t}} \tag{6}$$

Equation 6 implies that consumers are "investing" their time while traveling, which they value proportionally to their working time. Therefore, as per capita income increases, households prefer faster transport modes [46]. Currently, it is only attributed to passenger transport.

Figure 1 provides a graphical representation of the impact of the parameters mentioned above (exponent,

[5] Influence of the community on the lifestyle of individuals, which might affect the preferences in vehicle choice.

[6] Annual costs including discounting.

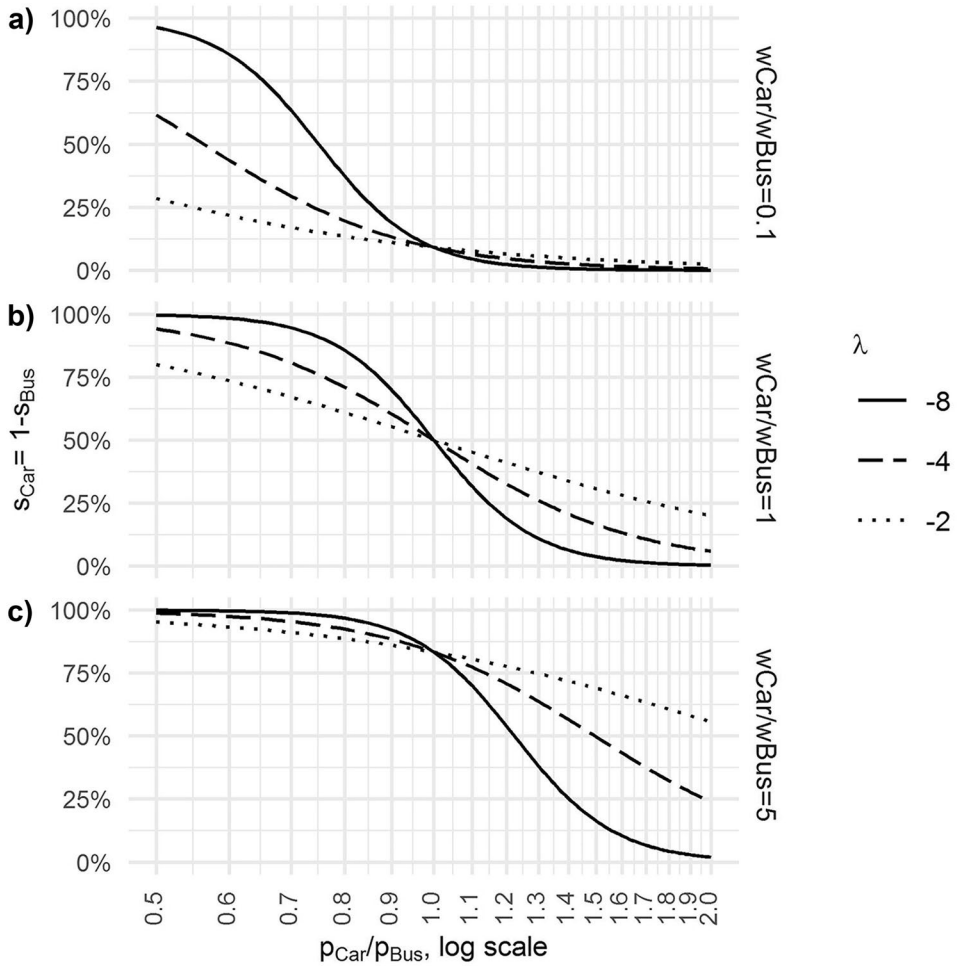

Fig. 2 The market share of cars as a function of the ratio between car price and bus price in a two-node nest, for different values of λ. Three cases are represented: low preference for cars (**a**), equal preference for cars and buses (**b**), and high preference for cars (**c**). λ influences the steepness of the curves; W ratio influences the sensitivity to price ratio change. The x-axis is on a $\log_{10}$ scale

preference factors, and prices). In this example, we consider a two-node nest, where private cars compete with buses to supply road passenger demand. On the x-axis in Fig. 2a–c, we report the ratio between car price and bus price, on the y-axis the market share of cars. The three panels of Fig. 2 refer to the different relative values of preference factors for cars and buses, respectively. The range of line styles represent different values ofλ, i.e., -2 (dotted), -4 (dashed), and -8 (solid). In all cases (Fig. 2a–c), high λ in absolute value determines a high sensitivity to a variation in price ratio (steep curves), while small λ is associated to small sensitivity to price variation (flat curves). The effect of preference factors is evident when comparing panel (a) with (c): strong preference towards buses ($W_{\text{Bus}} \gg W_{\text{Car}}$, Fig. 2a) leads to $s_{\text{Car}} \ll s_{\text{Bus}}$ if buses and cars are equally expensive ($p_{\text{Car}}/p_{\text{Bus}} = 1$). The opposite occurs for $W_{\text{Car}} \gg W_{\text{Bus}}$ (Fig. 2c): cars gain a high market share ($s_{\text{Car}} \gg s_{\text{Bus}}$) at $p_{\text{Car}}/p_{\text{Bus}} = 1$. Curves are symmetric at $\log\left(p_{\text{Car}}/p_{\text{Bus}}\right) = 0$ if the weight attributed to both alternatives is equal ($W_{\text{Car}}/W_{\text{Bus}} = 1$, Fig. 2b): in this configuration, a decrease and an equal increase in price of cars have the same effect in terms of $|\Delta s_{Car}|$. In Fig. 2a–c, for $p^{\lambda}_{\text{Car}} \equiv p^{\lambda}_{\text{Bus}}$ the shares of cars and buses are indifferent to λ as prices are simplified as shown in Eq. 1 and s_{Car} is only a function of W_{Car} and W_{Bus}.

The resulting prices for the aggregate node (road) are given by the weighted average of the sub-nodes,

$$p_{\text{Road}} = s_{\text{Car}} p_{\text{Car}} + s_{\text{Bus}} p_{\text{Bus}} \tag{7}$$

Please note that the nested function does not minimize the aggregate cost p_{Road}: it performs the most cost-effective choice at every given level, but this does not necessarily imply that the upper-level cost will be minimized, as represented graphically in Fig. 3. In Fig. 3a, we report the market shares for cars and buses as a function of the price ratio of the two alternatives, and in Fig. 3b the price of the top node (road) along with the partial price of cars and buses (respectively $s_{\text{Car}}p_{\text{Car}}$ and $s_{\text{Bus}}p_{\text{Bus}}$). W is set to 1 for both cars and buses, $\lambda = -8$, and $p_{\text{Bus}} = 0.5\$/\text{pkm}$ (constant). For every given combination of p_{Car} and p_{Bus}, the shares of cars and buses are allocated according to Eq. 1 in a cost-effective way (e.g., higher price leads to lower share). However, the total price is not monotonous:

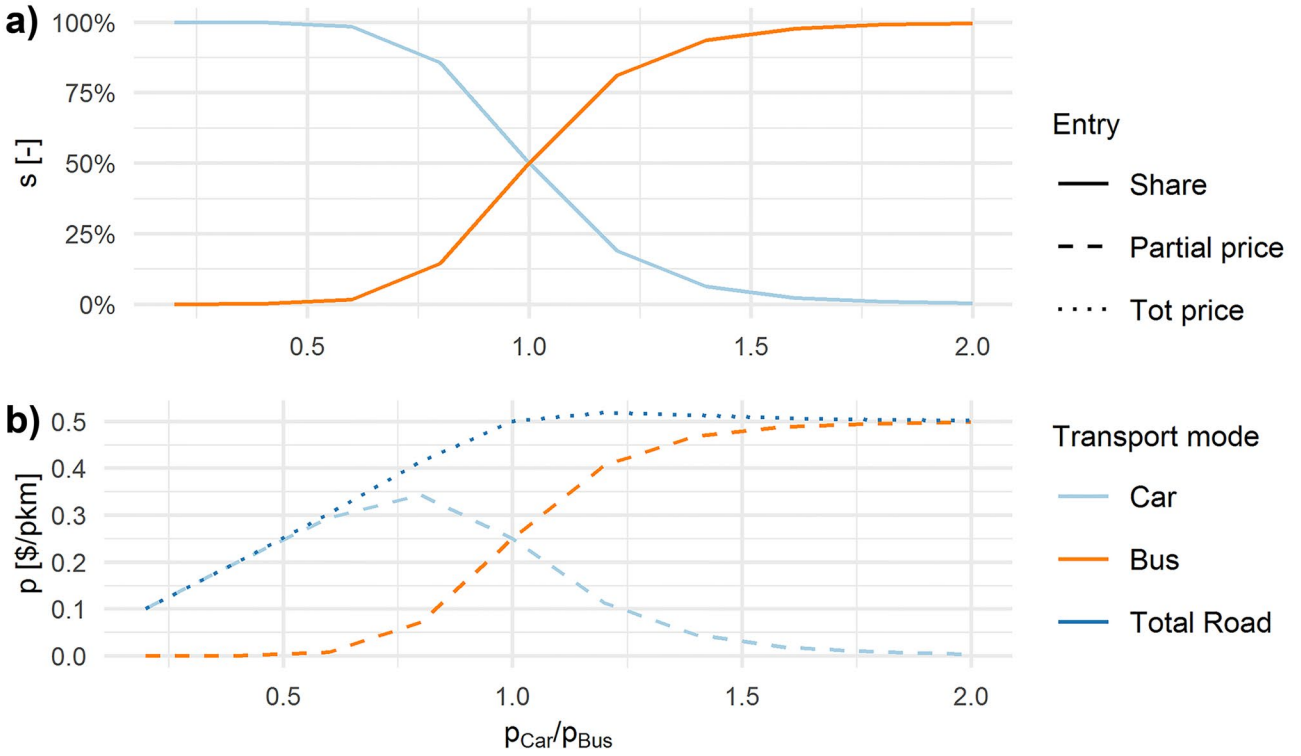

Fig. 3 Share of cars and buses on total road transport (**a**) and price of transport mode (total road and partial car and bus) (**b**) as a function of the ratio between Car and Bus price. Partial price represents $p_i \cdot s_i$ for i in car, bus, while total price represents the aggregate road price as in Eq. 7. Total price does not decrease monotonously for car price decreasing (from right to left on the x-axis), given constant Bus price. The x-axis is on a $\log_{10}$ scale

following the x-axis from right to left, as cars become increasingly cheaper, road price slightly increases at first and then decreases.

3.2 Total Demand Projections

EDGE-T provides estimates of total energy service projections through the following regression formulations for country c and time step t.

For passenger transport, the demand is calculated as

$$D_{c,t} = \overline{D}_c \left(\frac{g_{c,t}}{g_{c,t-1}} \right)^{\alpha} \left(\frac{p_{c,t}}{p_{c,t-1}} \right)^{\beta} \left(\frac{Q_{c,t}}{Q_{c,t-1}} \right) \tag{8}$$

while for freight transport, the adopted equation is

$$D_{c,t} = \overline{D}_c \left(\frac{G_{c,t}}{G_{c,t-1}} \right)^{\alpha} \left(\frac{p_{c,t}}{p_{c,t-1}} \right)^{\beta} \tag{9}$$

where $D_{c,t}$ is the energy services demand, $\overline{D}_c$ represents a calibration value for demand in the base year, α is the income elasticity, β is the price elasticity, $G_{c,t}$ and $g_{c,t}$ are the GDP and per capita GDP, respectively, $Q_{c,t}$ is population, and $p_{c,t}$ is the transport price. As can be seen from Eqs. 8 and 9, a price trend estimate is required as an input, along with assumptions on the socio-economic developments (i.e., population and GDP), from today until 2100. The demand trend is estimated by regression analysis using the income and price elasticities in Table 5.

[1]Based on [43] value for aviation

[2]High-income countries, based on [43]: average value of a fleet consisting of 65% LDVs, 12% aviation, 12% buses, 12% rail

[3]Low-income countries

Table 5 Price and income elasticity for all transport aggregate modes. Values from [32] unless noted otherwise

Transport mode	Income elasticity	Price elasticity
Passenger	Long distance: 1.01[1] Short-medium distance: 0.4[2]–1.00[3]	Long distance: −1.00 Short-medium distance: −1.25
Freight	Long distance: 0.40 Short-medium distance: 0.75	Long distance: −0.65 Short-medium distance: −0.65

3.3 Vintages Calculation for LDVs

The fleet is explicitly tracked for light-duty vehicles, the average lifetime of which is assumed to be 15 years. Vintages are calculated in annual time steps, to enable a better representation of the fleet turnover. The depreciation factor for each year is calculated according to the following equation:

$$d_y = 1 - \left[\frac{(y - 0.5)}{l}\right]^4 \tag{10}$$

where d_y is the depreciation factor, y is the year, and l is the vehicle lifetime. We calculate the composition of the last historical year (2010) assuming that the new additions were constant for the previous 14 years and equal to the new additions in 2010. This assumption is in line with figures from [47]: considering the fleet composition in 2016 divided by age groups, each country shows similar figures of passenger cars registered in 2014, 2015, and 2016. If we assume low depreciation for this short time range, this is an indication of rather stable vehicle additions each year for most European countries.

In case the depreciated fleet inherited from the previous time steps is higher than the total demand for LDVs projected for the following time step, a mechanism of early retirement decreases the inherited stock to ensure that 10% of the current fleet is newly added, thus avoiding the unrealistic configuration with 0% sales.

The vehicle mix resulting from the vintages calculation is therefore based on the formulation described in Sect. 3.1, which is applied to the new additions of each year. The overall fleet composition is therefore derived from the market shares gained by each alternative in the current year's sales, and the composition of the previous years' sales, depreciating in time. As a consequence, vintages increase the inertia of the system.

3.4 Input Data Calibration and Evolution in Time

3.4.1 Learning by Doing and Its Influence on Costs

Battery electric LDVs are assumed to be subjected to learning effects, which only apply to the battery component of the non-fuel cost of a battery car. We assume that batteries represent 20% of the total purchase price for each vehicle type, and purchase price represents 80% of the non-fuel price in Eq. 5. The total volume of battery cars at a global level decreases costs in each country, implying a full spillover effect.

3.4.2 Preference Factor Evolution in Time

Preference factors are calibrated from historical observations, and therefore reflect the historical status of the transport system in each region. For developed countries, which have mature transport systems—i.e., per-capita mobility is relatively high and the basic infrastructures are not expected to drastically change—we may assume time-independent preference factors as a baseline trend. For developing countries, however, the major changes expected in future per-capita GDP, along with economic development, urbanization, population growth, and extensive infrastructure investments, are likely to impact on mobility demand patterns [1]. Under the assumption that developing countries will catch up with richer economies (convergence hypothesis, see among others [48]), consumption patterns will likely also resemble each other. To this end, we model their preferences to converge over time to the ones observed in comparable developed countries by 2100. We take into account that the preference for specific modes is influenced by the territorial morphology [49–51]: a relatively uniformly densely populated region like Europe offers more grounds for a diffused rail system, which is hindered by sub-urban sprawl in vast regions like the USA. We identify clusters of regions on the basis of their population density in 2015, and implement convergence for all regions in each cluster to the region with highest per capita GDP.

For the vehicle powertrain selection, we apply a slightly different approach. Preference factors at the technology level directly represent household acceptance. The gradual increase of the preference factors is equivalent to a reduction in the inconvenience cost over time following Eq. 3. Note that infrastructure is not directly represented in EDGE-T, but REMIND accounts for the fuel transport and distribution infrastructure capacity needed. A more detailed description of the preference factors assumptions is provided in the Appendix (A2).

4 Coupling Mechanism Design

The coupling mechanism is designed to improve the modeling of transportation projections within the full macroeconomic system. Given the structure of REMIND's calibration routine, (see Sect. 2), this also requires the definition of a baseline transport demand trend. To this end, there are two realizations of EDGE-T: (i) as a stand-alone model, applicable for the calibration of REMIND, and (ii) as a model coupled to REMIND in a system that provides detail on the transportation sector's energy requirements. The two model realizations are represented in Fig. 4 and discussed in detail in the following paragraph.

Standalone (calibration) Mode: EDGE-T can be used as a standalone model or to calibrate REMIND in the baseline scenario (Fig. 4a). During the REMIND calibration process, the CES efficiency parameters are adjusted until the model replicates exogenous demand trends [52]. A set

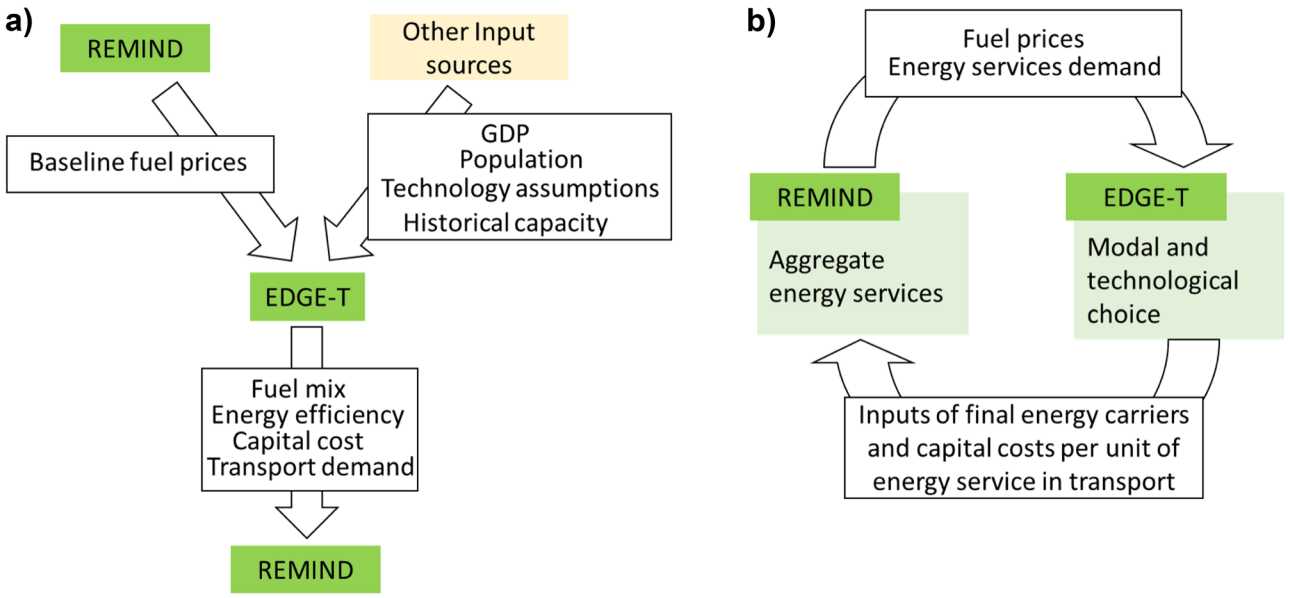

Fig. 4 The working principle of EDGE-T and REMIND in calibration or standalone mode (**a**) and in iterative mode (**b**). In **a**, REMIND and other input sources provide EDGE-T with the required input data, and EDGE-T provides the fuel mix, capital costs, energy efficiency, and total transport demand for REMIND calibration. In **b**, EDGE-T runs in between REMIND iterations: REMIND informs EDGE-T about fuel prices and total energy services demand; EDGE-T delivers to REMIND the mix of energy carriers required by the transport sector, and its energy efficiency and costs per energy services unit

of demand-focused models, called EDGE models (Energy Demand G*e*nerators), provides REMIND with sector-specific energy demand pathways. Three EDGE models have been developed in the past years to obtain sector-specific demand trends: EDGE-Buildings [52, 53], EDGE-Industry (Pehl et al., in preparation), and EDGE-T. In the calibration mode, EDGE-T calculates the fuel mix demanded by the transport sector, the associated costs, energy efficiency, and total transport energy demand (based on Eqs. 8 and 9). The input data that are required for the standalone mode include fuel prices (e.g., from previous REMIND runs), socio-economic parameters, and technological development parameters. A full list including the sources that have been used for the results in this work are given in Table 3.

Iterative Mode: In a coupled run, EDGE-T runs in between REMIND iteration (Fig. 4b). During each iteration, REMIND performs an intertemporal optimization over the full time period (2005–2150). In between iterations, it provides a complete set of prices to EDGE-T, which in turn uses the fuel prices to calculate the resulting market shares of the different vehicles and fuels (Eqs. 5 and 1). EDGE-T delivers to REMIND the mix of energy carriers required by the transport sector, and its energy intensity and costs per kilometer, calculated on the basis of the detailed Weibull-based share calculation. Convergence is reached after a series of iterations between REMIND runs and EDGE-T runs. To suppress fluctuations due to the coupling (flip-flopping), EDGE-T is set to run every 5th REMIND iteration. In Fig. 5, the flow of information from EDGE-T to REMIND is represented in more detail. EDGE-T determines the energy efficiency of the conversion from Final Energy to Energy Services for each energy carrier and each CES node. EDGE-T also determines the composition of the fuel mix that is demanded by each node of the CES structure: the available energy carriers among liquids, gases, power, and hydrogen are set to sum up to 1 for each CES node. Both energy efficiency and fuel mix directly interact with the CES structure (blue arrow in Fig. 5). Capital costs for the vehicles in EDGE-T are accounted for as investments required for transportation (orange arrow in Fig. 5). REMIND then determines the total energy service demand, balancing the required investments in transport capital and fuel provisions on the one side against the associated utility from the aggregated transport CES node. In between iterations, the costs of BEVs are adjusted in EDGE-T according to the learning rate applied to the cumulative amount of batteries in the fleet.

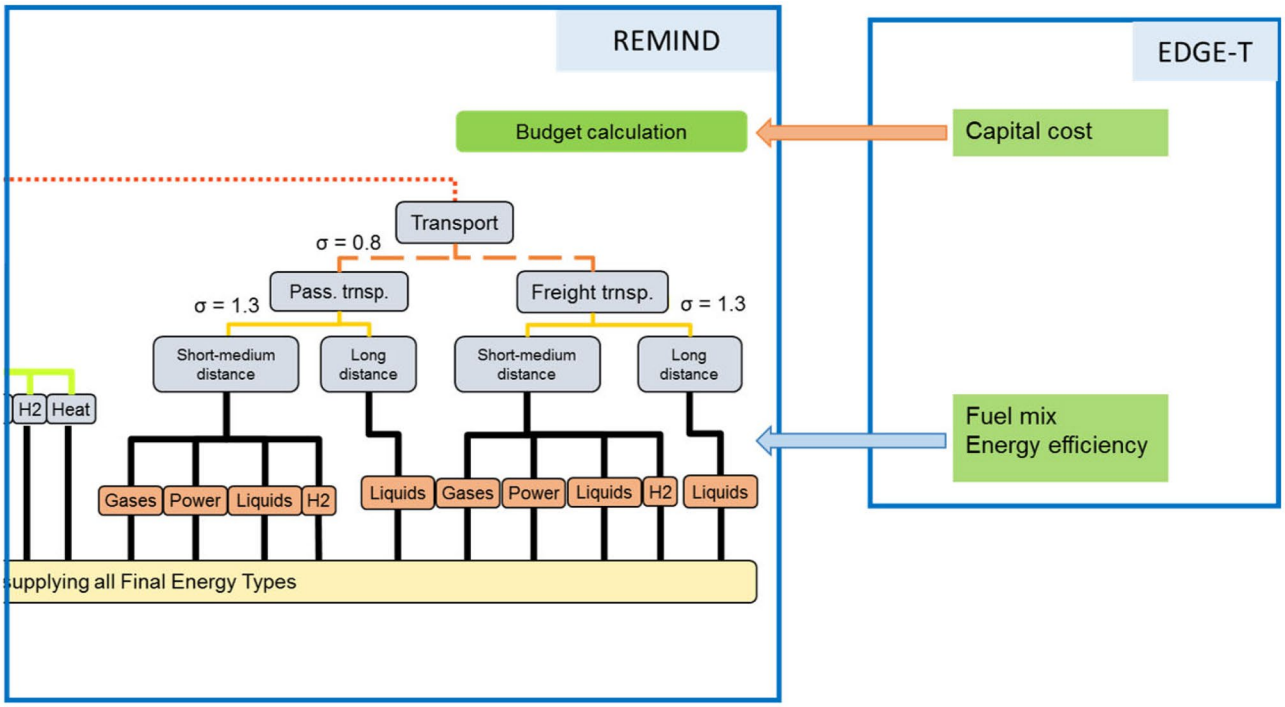

Fig. 5 The flow of information from EDGE-T to REMIND. EDGE-T determines the energy efficiency of the conversion from Final Energy to Energy Services and the composition of the fuel mix that flows in the transport branch of the CES structure (blue arrow). Capital costs are accounted for as transport-related investments on the budget equation (orange arrow)

5 Performance

In this section, we present the results we obtain from the REMIND/EDGE-T system. We perform a diagnostic analysis of the coupled system, aiming to assess the computational performance and the quality of the convergence.

5.1 Computational Performance

Apart from EDGE-T, three other algorithms modify the state of the REMIND model between iterations of the solver: (1) the clearing of international markets disturbs the optimization for the regions, (2) emission reduction targets can lead to changing regional CO_2 tax curves for regions, and (3) the coupling to the land-use model MAgPIE [54]. In the following paragraphs, we compare the REMIND/EDGE-T system to REMIND without coupling to EDGE-T (standalone).

We report the computational performance of the coupled REMIND/EDGE-T system compared with the performances of REMIND standalone, based on the CES structure as in [23]. REMIND standalone runtime is between 1h 30 min and 3 h for a 12-region setup on 12 cores with shared memory allocation, depending on the scenario settings and the starting point provided to the optimization. On average, the number of iterations per run is between 30 and 40. A REMIND/EDGE-T coupled run requires between 10 and 20% more than standalone runs for 40 iterations in a baseline scenario. The increase in runtime can be explained by the additional runtime of EDGE-T: An EDGE-T run lasts around 90 s, there are 8 runs in 40 iterations leading to a share of 12 min compared with a 90 min baseline run without EDGE-T. For REMIND runs with additional boundary conditions, i.e., climate policies, the REMIND runtime increases and the fraction of the EDGE-T runtime further decreases. We are thus confident that the computational burden of the EDGE-T coupling is moderate.

5.2 Convergence Performance

EDGE-T modifies the state of REMIND between iterations. In order to understand if the models are converging towards a common optimal solution, we identify a measure of the convergence stability and use this measure to pinpoint problems for specific regions, timesteps, and markets. In general, the two most prominent quantities which take part in the coupling cycle (Fig. 4) can be used to assess the market stability: (I) fuel prices as given by REMIND or (II) shares of specific fuels in the transport sector supply as derived by EDGE-T. We choose to focus on fuel prices as they are a direct output of the solving procedure. As a measure, we apply the standard deviation in the iteration domain for region r, timestep t, and fuel type i, i.e.,

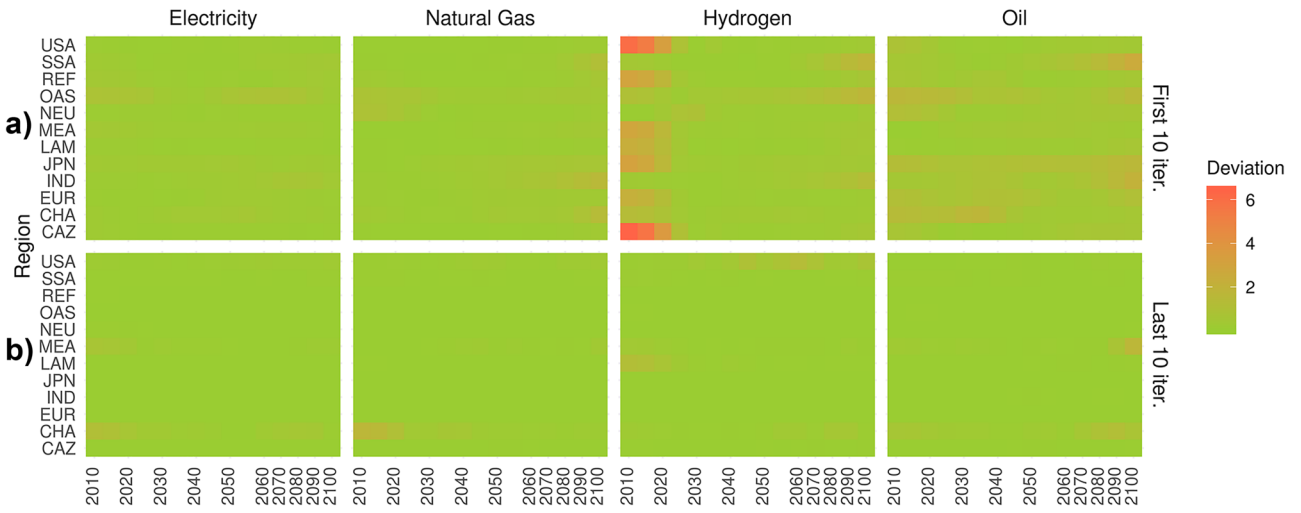

Fig. 6 Standard deviation as in Eq. 11 for the fuel price level of different fuels for all REMIND regions from 2010 to 2100. For the region definition, the reader is invited to refer to the Appendix

$$\delta_{r,t,i}^{N,m} = \sqrt{\frac{\sum_{k=m}^{N} \left[p_{r,t,i,k} - \overline{p}_{r,t,i}\right]^2}{N - m + 1}} \tag{11}$$

where $\delta_{r,t,i}$ represents the standard deviation, $p_{r,t,i,k}$ is the fuel price in iteration k, and $\overline{p}_{r,t,i}$ is the average value of the fuel price across iterations. N is the total number of iterations. In Fig. 6a, we report $\delta_{r,t,i}^{10,1}$, i.e., the deviation for 12 regions and years 2010 to 2100 in the first 10 iterations, and in Fig. 6b $\delta_{r,t,i}^{29,20}$ is shown. High deviation (red) implies variability in the fuel price trend, low deviation (green) indicates quite stable prices. As a general trend, fuel prices show some variability in the first 10 iterations (Fig. 6a), while prices are more stable in the last 10 model iterations (Fig. 6b). The most critical case is represented by hydrogen in the first 10 iterations, which shows significantly high deviation level for many countries and in selected time steps (Fig. 6a). The regions CAZ and USA, for time steps between 2010 and 2020, show the highest variability. Low deviations are reached in the last 10 iterations for all combinations of region, time step, and fuel (Fig. 6b). In Fig. 7, we report fuel price in the most critical case (USA, hydrogen) in the iteration domain for the critical year 2015 and in 2100 as a comparison. In Fig. 7, values for 2015 show a significant variability, but the price becomes increasingly stable towards the last iterations. Values for 2100 are quite stable until iteration 20, then have a negative spike, and later stabilize around the former stability level.

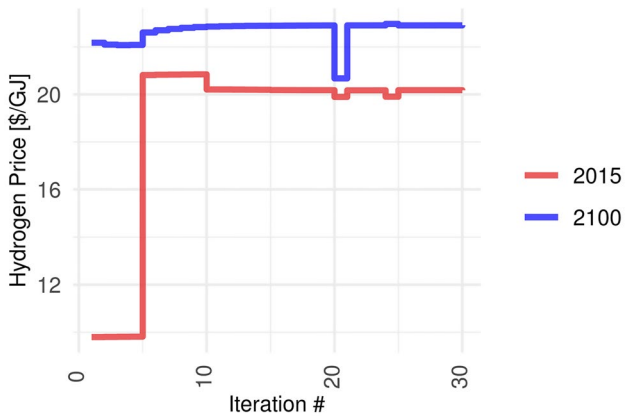

Fig. 7 Electricity price variation across iteration for USA, for the critical years 2015 and 2100. The initial iterations show a significant variability in 2015 that smoothens down gradually leading to a quite stable price in the last 10 iterations

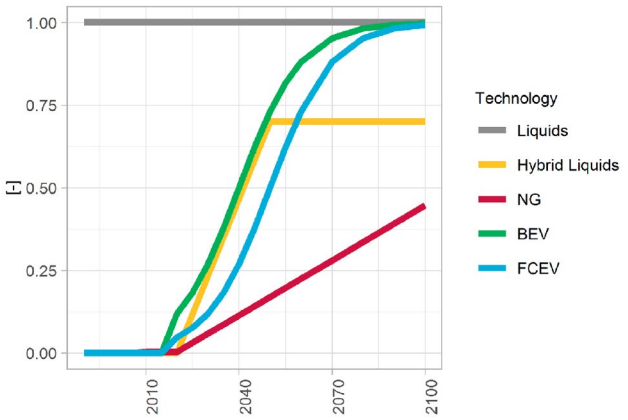

Fig. 8 Preference trend at technology level for Europe, in the illustrative case of LDVs. Consumers equally prefer BEVs and FCEVs by the end of the century. The takeover of hybrid liquids and NG is instead limited

6 Simulation Results

In this section, we report on preliminary results from a reference model run, with a focus on Europe and BEV diffusion in the market. Results indicate that the system REMIND/EDGE-T produces results well in line with other studies. We performed a comparison exercise between the REMIND/EDGE-T system (referred to as RE-T) and the 2016 EC Reference scenario (referred to as EURef) [55]. The set of preference factors for technology adoption in this scenario is reported in Fig. 8 for the representative case of LDVs. Concerning hybrid engines and natural gas engines, we set the preference factors to linearly grow over time, until reaching a saturation level. Electric railway evolves similarly, catching up to fossil-fueled railway. Concerning BEV and FCEV cars, we model the preference factors following S-shaped (logistic) curves.[7] This trend emulates the diffusion of new technologies and has already been applied to alternative technologies in the automotive industry [55]. A more detailed description of the preference factors trend is provided in the Appendix (A2).

In Fig. 9, we present the values for energy services demand[8] in Europe for EURef and RE-T, both for freight (Fig. 9a) and passenger transport (Fig. 9b), aggregated by transport mode. In terms of freight demand, RE-T results are closely aligned with EURef for 2015 (the first projected time step) as well as 2050. As for Passenger demand, RE-T slightly overestimates energy services demand values with respect to EURef in both 2015 and 2050. In Fig. 10, we report the final energy demand values of EURef, RE-T, and a REMIND standalone run, based on the model prior to EDGE-T implementation (referred to as RS). RE-T shows a higher energy demand than EURef, both in

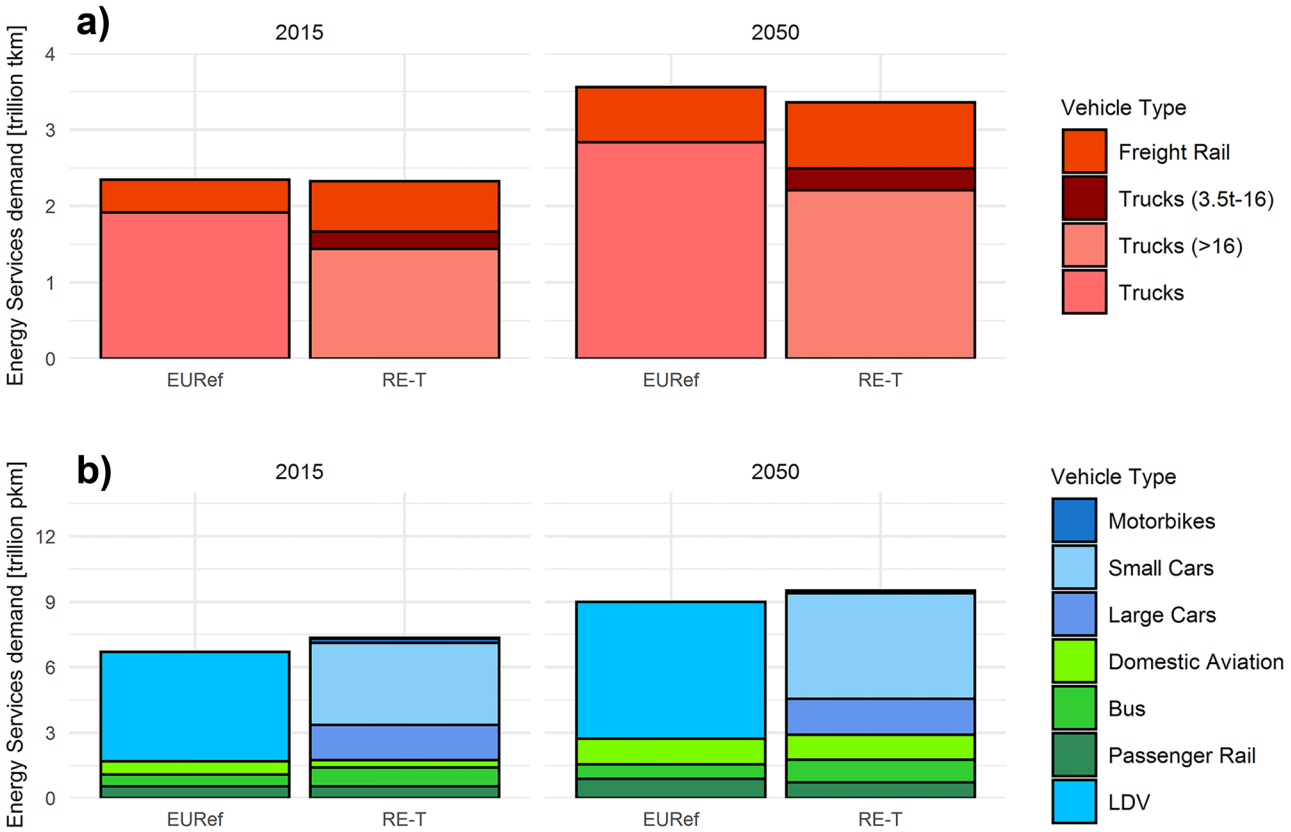

Fig. 9 Energy services demand for selected transport mode in a baseline run for Europe, in the reference scenario EURef and in EDGE-T, for freight (**a**) and passenger (**b**). For freight demand, the EDGE-T regression is very much in line with EURef for both 2015 and 2050. For passenger demand (Small cars include compact cars, subcompact cars, mini cars; large cars include large cars, SUVs, vans, and midsize cars.), the RE-T regression slightly overestimates the energy services demand in 2015 with respect to 2016EU-Ref, but results in 2050 are quite in line for the two models

[7] Infrastructure is not directly represented in EDGE-T, but REMIND accounts for the fuel transport and distribution infrastructure capacity needed.

[8] International aviation and international shipping are not included.

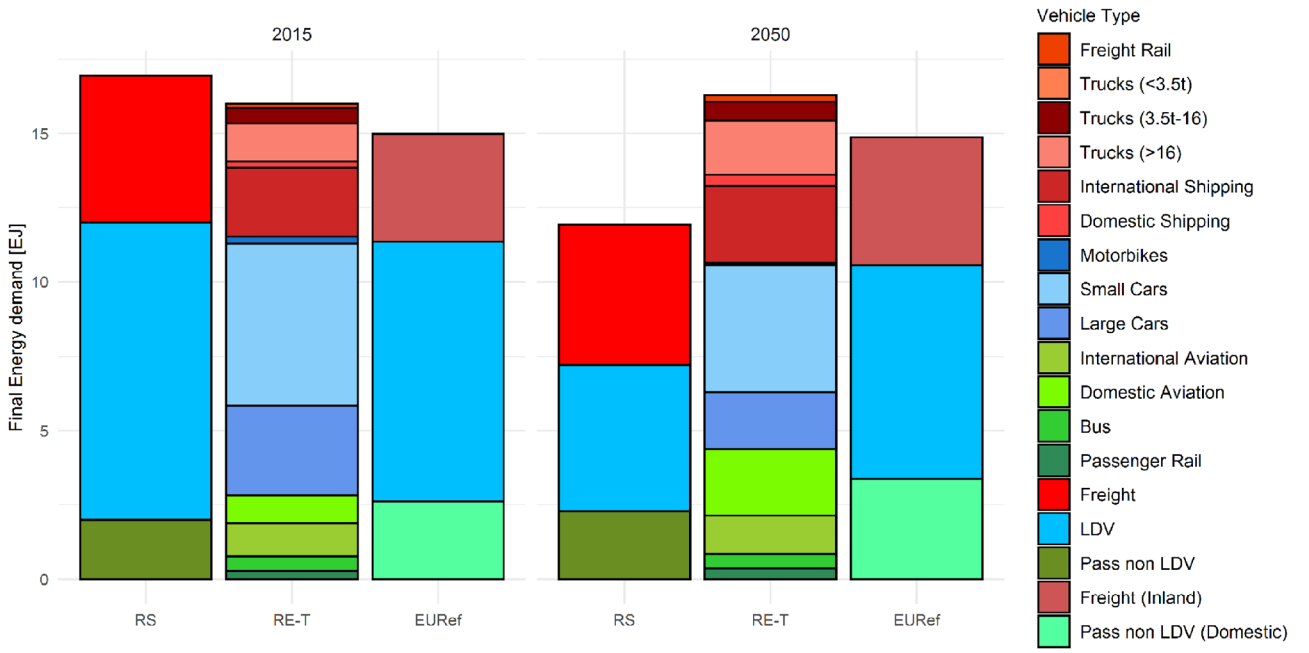

Fig. 10 Final energy demand for the transport sector in a baseline scenario in a REMIND standalone run (RS), in a coupled run REMIND/EDGE-T (RE-T) and in the 2016 EU Reference scenario (EURef). RE-T demand is shown in the detailed composition (Small cars include compact cars, subcompact cars, mini cars; large cars include large cars, SUVs, vans, and midsize cars.), RS and EURef are given in aggregate values (international shipping and aviation for EURef are integrated with own calculations.)

2015 and 2050. Comparing RE-T with EURef, energy demand for freight is higher in RE-T than in RS for both 2015 and 2050. The difference could be related to the different values of energy efficiency across the two models, as well as to the absence of inland navigation[9] in RE-T. RS shows on the other hand slightly overestimated values in 2015 with respect to both RE-T and EURef, while it projects significantly lower values for both Passenger non-LDV demand and LDV demand in

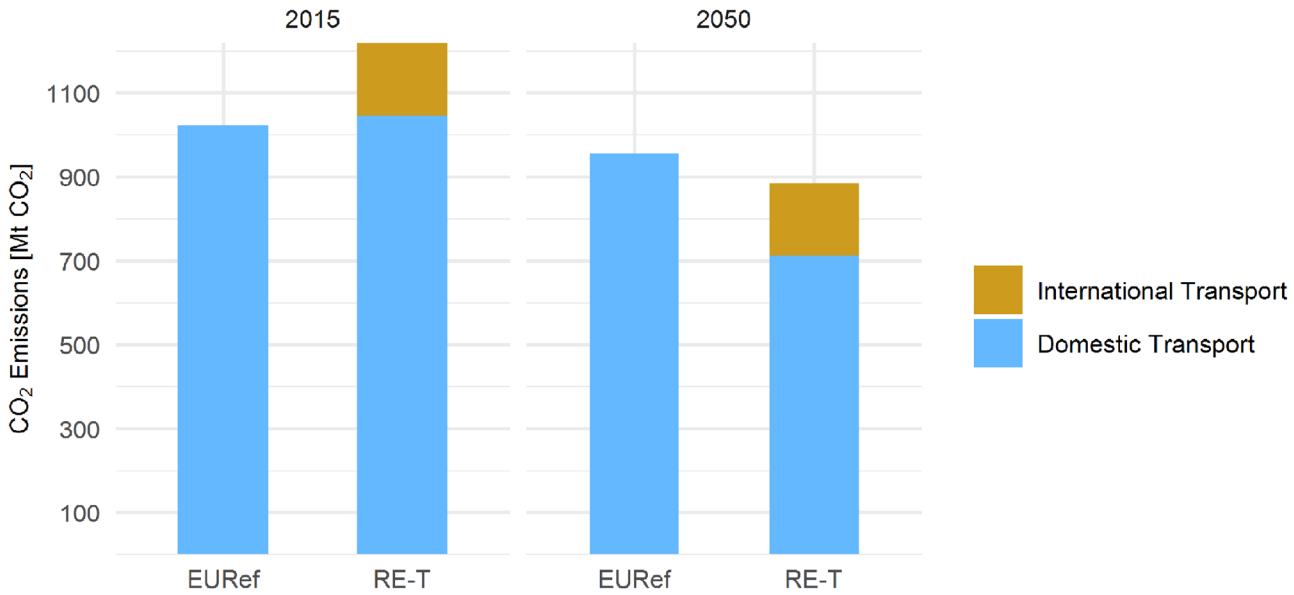

Fig. 11 Total CO_2 emissions from transport sector in Europe, divided into Domestic and International transport (Bunkers)

[9] Passenger and freight transport on lakes and rivers.

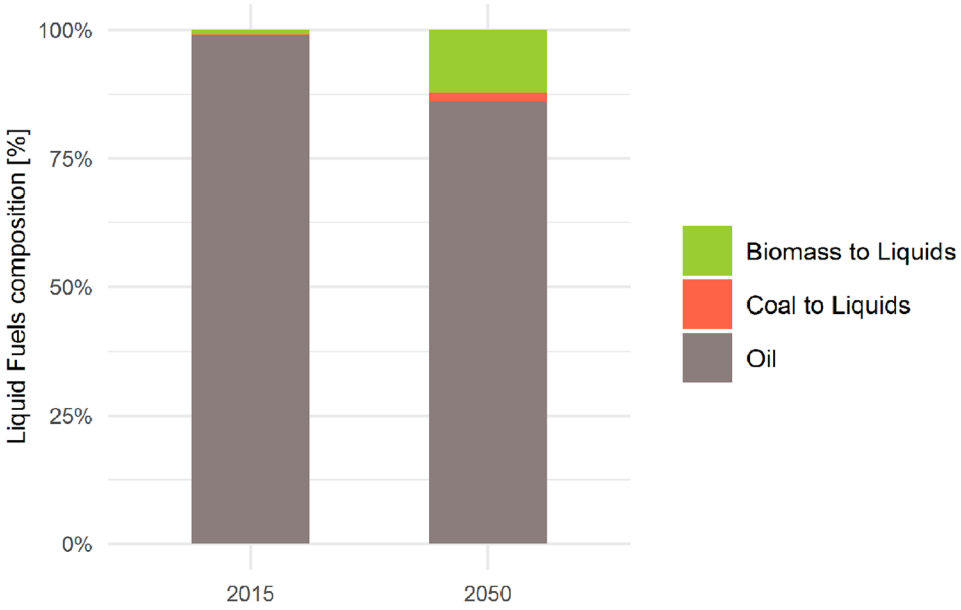

Fig. 12 Liquid fuels composition in a coupled run REMIND/EDGE-T

2050. This is a consequence of the purely (fuel- and vehicle-) price-driven decision-making process of REMIND. In RS, BEV and FCEV cars enter the market along an exogenous trajectory and are widely adopted as soon as the vehicle prices become competitive, resulting in a low final energy demand.

Total CO_2 emissions from transportation are reported in Fig. 11, for RE-T and EURef. Emissions are reported separately for domestic and International transportation, when available. While both models see a limited increase in demand, the resulting emissions vary due to varied shifts towards low-carbon options. Emissions from domestic transport show a 30% decrease from 2015 to 2050 in RE-T, while the decrease is less pronounced in EURef with only 10% reduction. The decrease in emissions in RE-T has two main drivers: the increasing importance of biofuels, and the significant share of advanced and alternative fuel vehicles. In Fig. 12, we report the percentage of different sources for liquid fuels in 2015 and 2050: more than 10% of liquids in 2050 come from biomass. In Fig. 13, the LDV mix composition is represented by powertrain, distinguishing between previously bought vehicles (vintages) and annual new additions. By 2050, alternatives such as BEVs, FCEVs, and Hybrids gain market shares of around 20%, 5% and 20% of the fleet, respectively.

High uncertainty exists, however, on the deployment of alternative vehicles, both in terms of technological

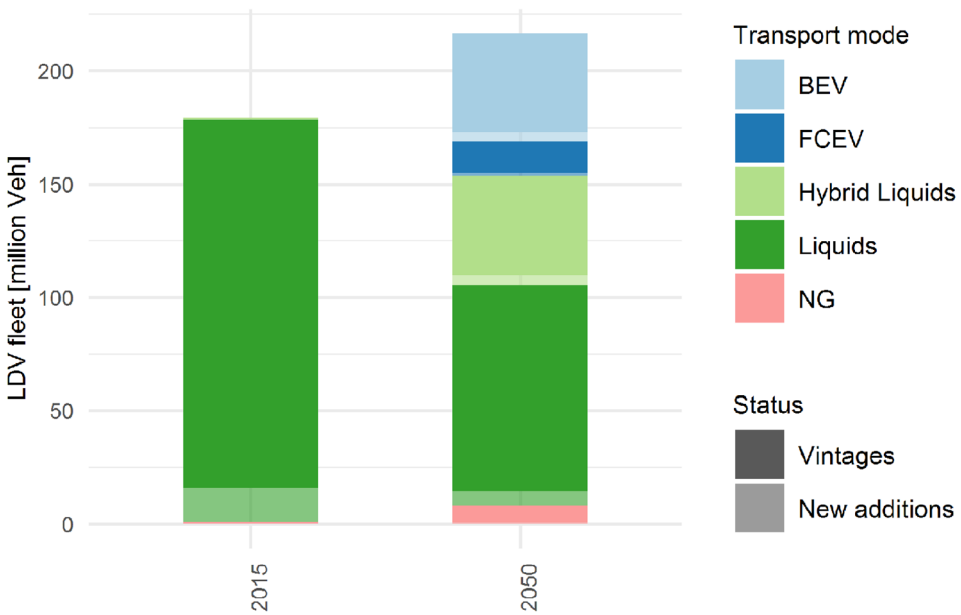

Fig. 13 LDV composition in Europe by powertrain, divided in Vintages (solid fill) and yearly New additions (faded fill), in a coupled run REMIND/EDGE-T

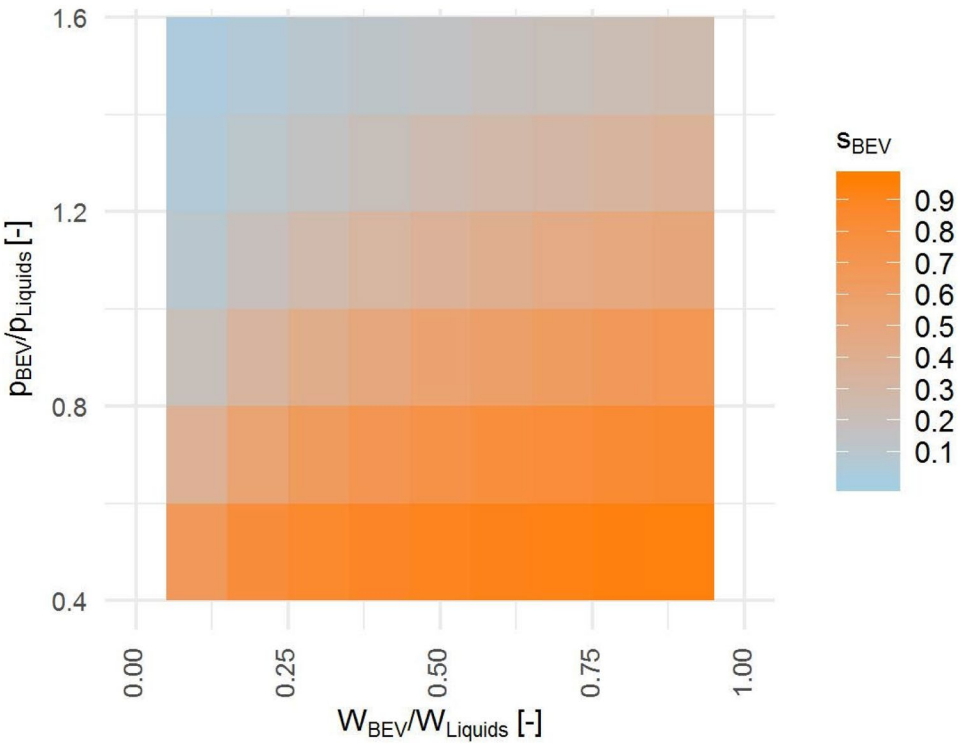

Fig. 14 Sensitivity analysis on the costs and acceptancy of BEV cars. *Y*-axis: ratio between an average BEV car and an average ICE-car. *X*-axis: ratio between acceptancy of BEVs and ICEs. Fill: share of BEV cars

improvements (and the corresponding cost savings), consumer acceptance, and infrastructure availability. To test the range of possible costs and acceptancy values of BEVs, we perform a sensitivity analysis to determine the relative influence of the preference factor and the non-fuel costs, on BEV market share in 2050 (Fig. 14). For this sensitivity analysis, prices and preference factors for all other technologies are left unchanged, and BEVs are compared with the strongest competitor in the market, ICE cars. The price of BEVs is set to vary between 40 and 160% of an ICE car, while preferences for BEV range from 0 (very low acceptance) to indifference from ICE cars ($W_{\mathrm{BEV}}/W_{\mathrm{ICE}} = 1$). At equal prices ($p_{\mathrm{BEV}}/p_{\mathrm{ICE}} = 1$), high acceptance ($W_{\mathrm{BEV}}/W_{\mathrm{ICE}} \cong 1$) would lead BEVs to gain almost 40% of the market, while ICE (traditional and hybrid) retain around 60%. Lower prices of BEV cars ($p_{\mathrm{BEV}}/p_{\mathrm{ICE}} < 1$) push the market towards BEVs, even at low acceptance rates ($W_{\mathrm{BEV}}/W_{\mathrm{ICE}} \ll 1$); at $W_{\mathrm{BEV}} \sim 10\% W_{\mathrm{ICE}}$ and $p_{\mathrm{BEV}} \sim 0.5 p_{\mathrm{ICE}}$, the share of BEVs would be around 50%.

7 Conclusions and Further Developments

In this work, we describe the newly developed EDGE-T model and the coupling mechanism with the Integrated Assessment Model REMIND. The coupled system represents a consistent framework in which competition for scarce resources (fuels, CO_2 emissions in a mitigation scenario), socio-economic development, and transport demand interact. The coupling enhances the global full-system IAM-based scenarios by providing a much higher level of detail on the different transportation modes and vehicle choices, and creates a consistent modeling framework that enables representation of behavioral aspects and detailed policies. The additional computation burden remains moderate. We perform a diagnostic of the coupling mechanism, analyzing the quality of the convergence. The modifications of the internal state are accompanied by initial fluctuations which die out gradually in later iterations and eventually the system converges towards a stable solution in the cases studied for this work. Results indicate that for the current parametrization and in the absence of specific policy measures, the REMIND-EDGE-T system anticipates an increase in energy services demand in Europe of about 20% for passenger transport and 40% for freight between 2015 and 2050, in line with the EC Reference 2016 scenario [55]. Emissions from the transport sector decrease by 30% with respect to 2015 values due to advancements in technology, increased acceptance levels of alternative vehicles, and a shift to bioliquids. Penetration of BEV cars reaches 20% of the fleet in 2050, while internal combustion engines (both traditional and hybrid) retain 75%. A sensitivity analysis on the influence of consumer preferences underlines their important role for EDGE-T model outputs.

The preliminary REMIND/EDGE-T results already provide interesting insights on the possible development of the transport system. Further developments to improve applicability of the tool for scenario-based policy analyses will focus mainly on consumer preferences. In the current implementation, technological and modal switches heavily depend on the initial calibration and the time path of the preference factors, which are set exogenously until 2100. The constituents of these factors are challenging to disentangle and rely on a host of ad hoc assumptions. For the plausibility of EDGE-T results, it is therefore key to improving the representation of preferences or inconvenience costs to endogenize mode switch and technology choice, and eventually distinguishing between the most significant barriers to alternative technology adoption.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10666-021-09760-y.

Author Contribution All authors contributed to the study design. All authors read and approved the final manuscript.

Funding Open Access funding enabled and organized by Projekt DEAL. The research leading to the study has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 73043 (INNOPATHS) and from the Volkswagen's independent Sustainability Council under the project "Transformation Towards Sustainable Transport Systems – The Next Generation Policies".

Availability of Data and Materials Data is not publicly available, but can be provided upon request.

Code Availability The REMIND model and the EDGE-T model are available on GitHub.

Declarations

Competing Interests The authors declare that they have no conflict of interest.

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