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Does size matter? The influence of size, load factor, range autonomy and application type on the Life Cycle Assessment of current and future medium- and heavy-duty vehicles.

Romain Sacchi[1*], Christian Bauer[1], Brian L. Cox[2]

1 = Technology Assessment group, Laboratory for Energy Systems Analysis, Paul Scherrer Institut, Villigen, Switzerland

2 = INFRAS, Bern, Switzerland

**Corresponding author: email - romain.sacchi@psi.ch, telephone - +417 67 62 19 22, fax - +41 56 310 21 99*

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Abstract

The transparent, flexible and open-source Python library carculator_truck is introduced to perform the life cycle assessment of a series of medium and heavy-duty trucks across different powertrain types, size classes, fuel pathways and years in a European context. Unsurprisingly, greenhouse gas emissions per ton-km reduce as size and load factor increase. By 2040, battery and fuel cell electric trucks appear to be promising options to reduce greenhouse gas emissions per ton-km on long distance segments, even where the required range autonomy is high. This requires that various conditions are met, such as improvements at the energy storage level and a drastic reduction of the greenhouse gas intensity of the electricity used for battery charging and hydrogen production. Meanwhile, these options may be considered for urban and regional applications, where they have a competitive advantage thanks to their superior engine efficiency. Finally, these alternative options will have to compete against more mature combustion-based technologies which, despite lower drivetrain efficiencies, are expected to reduce their exhaust emissions via engine improvements, hybridization of their powertrain as well as the use of biomass-based and synthetic fuels.

Keywords

battery, fuel cell, electric, open-source, freight, transport, tank-to-wheel, prospective

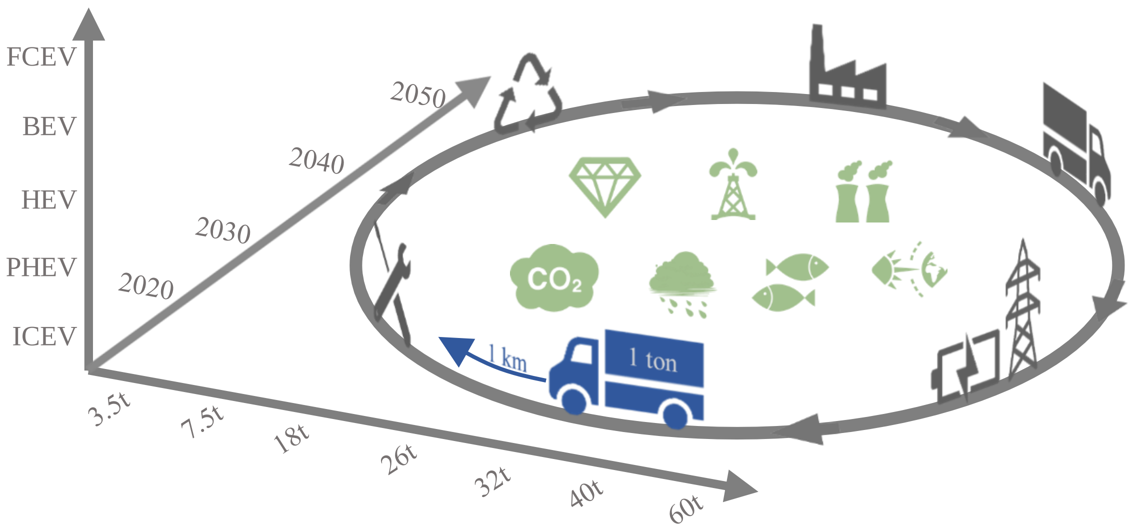
Acronyms

BEV	Battery electric vehicle
CCS	Carbon capture and storage
CNG	Compressed natural gas
FCEV	Fuel cell electric vehicle
GHG	Greenhouse gas
HEV-d	Hybrid engine vehicle, powered by diesel fuel
HPR	Heatpipe reformer
ICEV-d	Internal combustion engine vehicle, powered by diesel fuel
ICEV-g	Internal combustion engine vehicle, powered by compressed gas
LGV	Large goods vehicle
LNG	Liquefied natural gas
MGV	Medium goods vehicle
NMVOC	Non-methane volatile organic compounds
PHEV-d	Plug-in hybrid engine vehicle, powered by diesel fuel and electricity

Synopsis

Battery and fuel cell trucks can reduce GHG emissions from road transport substantially, but the actual reduction depends on developments in other sectors.

Abstract art



1 Introduction

Mitigating climate change impacts and keeping the atmospheric temperature increase under 2°C by 2100 (compared to 1990 levels) requires a substantial and fast reduction of anthropogenic greenhouse gas (GHG) emissions in all economic sectors [1]. Road transport is an important source of GHG emissions worldwide: in 2018, heavy duty vehicles (HDV) released 1,770 Mt of CO_2 via their exhaust emissions[2]. This represents more than 5% of the energy-related CO_2 emissions emitted that year [3]. Emissions from these vehicles exhibited an annual growth rate of 2.6% since the year 2000, as emissions reduction resulting from more efficient vehicles have been offset by an increase in economic activity and demand for goods [2]. In the European Union (EU), CO_2 emissions from HDV currently represent 6% of total CO_2 emissions and 25% of total road transport CO_2 emissions. To reduce these emissions and align with the long-term strategy of carbon neutrality in 2050, the EU has released a regulation with mandatory goals: fleet-wide average CO_2 emissions of new lorries registered shall be reduced by 15% and 30% in 2025 and 2030, respectively, compared to 2020 [4]. These goals are not achievable using conventional diesel trucks alone, despite expected efficiency gains, and in the long term, “zero-emission” vehicles such as battery electric (BEV) and fuel cell electric vehicles (FCEV) will be required.

However, these so-called “zero-emission” vehicles only exhibit zero GHG emissions during vehicle operation. Indeed, substantial GHG emissions are associated to the production of these vehicles as well as the fuel supply. This has been shown for passenger vehicles in the past [5–13]. There is now sufficient evidence that BEV and FCEV passenger vehicles can reduce life cycle GHG emissions, if batteries are charged with low-carbon electricity and hydrogen production is associated with low GHG emissions. However, because HDV differ from passenger cars in terms of specifications, operational requirements and function, the environmental life cycle performance of HDV might differ significantly.

Therefore, a thorough analysis is required for HDV as well. Regarding medium (MGV) and large (LGV) goods vehicles, literature on their life cycle environmental performance is scarce and limited in terms of temporal, technological and application scope. Several studies and tools have evaluated the life cycle environmental burden of (current) BEV trucks in comparison with non-electric technologies [14–19]. But the scope of these studies remained limited: some did not consider all size classes [14,15,18] or all powertrain types[17], other limited the supply of hydrogen to one pathway [16], while none included future perspectives. Additionally, the important relation between payload and energy storage requirements for BEV trucks, as demonstrated by Sripad and Viswanathan[20], seems largely ignored.

This overview shows that a comprehensive and consistent life cycle-based comparison of the environmental performance of trucks across drivetrains, fuel pathways and size classes is missing. Such evaluation should consider potential future development, since it is expected that BEV and FCEV will profit more substantially from future developments than mature conventional drivetrains. A comprehensive scope in terms of drivetrains and fuels together with a consistent evaluation framework are crucial, since the validity of comparison of results from different LCA studies is without further harmonization – often limited by different modeling approaches, background data, and assumptions.

This paper addresses these research gaps and presents *carculator_truck*, an open-source LCA model to analyze the life cycle environmental performance of MGV and LGV with an unprecedented scope, flexibility, transparency and level of detail. The model covers:

- Six powertrain technologies: diesel, diesel-hybrid, plugin diesel-hybrid, compressed gas, fuel cell and battery electric powertrains. This list gathers the most representative technologies on the current market (i.e., diesel and compressed gas), as well as probable future competing technologies (i.e., hybrid, electric and fuel cell powertrains), which are about to enter the market or expected to do so in the next few years – at least in the EU, BEV and FCEV trucks will be required to achieve fleet goals for reduction of GHG reduction. Liquefied natural gas (LNG) vehicles are not included as sources for emissions data are not robust enough and inventories for on-board energy storage are not readily available. It is however of the authors' opinion that the performance of CNG vehicles presented in this study can be a reasonable proxy for LNG vehicles.
- Seven size classes (referring to the gross vehicle weight): 3.5-ton delivery trucks, 7.5-ton, 18-ton and 26-ton rigid trucks, as well as 32-ton, 40-ton and 60-ton articulated trucks. MGV refers to vehicles with a gross weight between 3.5 and 26 tons, while LGV are vehicles with a gross weight above 26 tons.
- Three application types: urban and regional deliveries as well as long haul, associated to a range autonomy of 150, 400 and 800 km respectively. These default distances are chosen arbitrarily by the authors, as they seem to correspond well to each type of application. However, results can be produced for any other range values using the *carculator_truck* library – the energy storage of the vehicles will be sized accordingly.
- Over a period of 50 years, defined by six points in time (from 2000 to 2050 by 10-year steps). FCEV and BEV trucks are not modeled before 2020.

- With over twelve different fuel pathways: diesel, biodiesel, natural gas, bio-methane, electricity, hydrogen, synthetic fuels, etc.

This paper highlights the influence of size, range autonomy, technological improvement and duty cycle on the respective environmental performance of powertrain technologies and specific fuel chains.

2 Method

LCA consists in quantifying the release of environmentally harmful emissions of a product or service along each of the relevant phases of its life cycle. In the case of trucks, this includes the manufacture of their components, their assembly, the use and maintenance of the trucks as well as their disposal. These emissions are expressed in reference to a functional unit to offer a common basis for comparison between trucks of different technologies and sizes. The functional unit typically used to compare trucks is the transport of 1 ton of cargo over 1 km. These emissions are then characterized against indicators that reflect the burden and damage borne by mid- (e.g., Global Warming) and endpoint (e.g., Human health) recipients, respectively, via cause-effect pathways (e.g., from the emission of a greenhouse gas to the radiative forcing of the atmosphere). The process ranging from emissions inventory to impacts characterization is governed by a series of international standards, namely ISO 14040 [21] and ISO 14044 [22].

This study introduces *carculator_truck*, which is an open-source Python library that allows to perform LCA of MGV and LGV under different future energy scenarios. Its source code is hosted on an online public repository[23]. This ensures that the code, algorithms and assumptions behind the model can be viewed, criticized and improved by the community at large. A notebook using this library is included in the Supplementary Information (SI) to ensure that all the results and figures presented in this study are reproducible, provided the same version of the library is used (version 0.1.3 at the time of writing). This library operates similarly to *carculator*, another Python library for modeling life cycle impacts of passenger cars [6]. It mainly revolves around the following 3-step workflow:

1. Arrays that contain input parameters are loaded. The spectrum of input parameters is wide and listed in Table 1 of the SI. It includes, for example: parameters defining the efficiency of the engine, the mass of the battery charger, but also the energy density of battery cells. The arrays are three dimensional as the input parameters are defined across powertrains, size classes and years.

2. An algorithm iterates between components, dimensions and masses and the energy consumption of the vehicles, to find technically feasible solutions given a set of constraints. The set of constraints includes, among others, the minimum range autonomy for BEV or the CO_2 reduction targets for internal combustion engine vehicles (ICEV). At this stage, CO_2 and other exhaust and non-exhaust emissions (i.e., hot pollutants, noise) are calculated based on the selected driving cycle and the associated fuel consumption.
3. Once the vehicles are modeled, the total material and energy requirement for each truck is calculated. The inventories are characterized against midpoint (e.g., Climate change) or endpoint (e.g., Human health impacts) environmental indicators.

Each of these three points are discussed in the next sections. The validation of the vehicle models against literature data and existing vehicles is included in the SI.

2.1 Input parameters definition

Values for input parameters are stored for all vehicles across three dimensions: powertrain type, size class and year. Most of the values for these parameters are given with uncertainty distributions, making it possible to perform error propagation analyses. *carculator_truck* uses over 70 parameters to build 252 unique truck models (6 powertrain types, 7 size classes, at 6 points in time). Table 1 in the SI lists these parameters and whether their values change across powertrain types, size classes and years. Sources, values, uncertainty distributions and descriptions for these parameters are also included as a spreadsheet in the SI.

2.2 Sizing, energy consumption and emissions of vehicles

The next subsections describe how the vehicles are dimensioned and how the fuel consumption and emissions are calculated.

2.2.1 Mass distribution

First, the model brings together the components common to all powertrains. These include the chassis, the cabin, the onboard electronics, the suspension system, the brake system and the wheels and tires. Such components for diesel trucks across size classes are listed in Table 2 of the SI. The weight composition by components are the result of cross-checking several sources, as indicated in that same table. Most of the values are based on a 12-ton and 40-ton truck from [24,25], further adapted to other size classes for which curb and payload masses are known from the database Car2db [26]. Second, powertrain-specific components are added, such as the internal combustion engine and fuel tank for ICEV-d and ICEV-g, an electric motor with batteries for BEV trucks, or with a fuel cell stack and a hydrogen tank for FCEV trucks. For these components, the 40-ton truck model of Wolff et al. [25] is principally used. Across time, it is assumed that such composition does not change. However, a light-weighting factor is applied to the sub-components of the chassis system as listed in Table 2 of the SI, according to [24], going from 2 and 5% in 2020, to 28 and 30% in 2050 for MGV and LGV respectively, compared to 2010. To that effect, this weight reduction over time is modelled as steel being substituted by aluminium[27].

The sum of the mass of the vehicle components corresponds to the curb mass. The available payload is calculated as the gross vehicle mass, to which the curb mass, the fuel mass and the driver mass are subtracted. The actual cargo mass is the product of the available payload and the load factor. The sum of the curb mass, the fuel mass, the driver's mass and the cargo mass constitute the driving mass. As Table 1 of the SI shows, the load factor varies across truck sizes. Being a critically important parameter, it is recommended to adapt this load factor to the specific context of the assessment. For this study, load factors based on TRACCS' European average survey data are used and are as follows: 60%, 41%, 42%, 38%, 36% for 3.5t, 7.5t, 18t, 26t and 32t-60t trucks, respectively[28]. The TRACCS publication warns however that some uncertainty resides in such factors.

Because some of the vehicle components are scaled on the energy consumption of the vehicle (such as the fuel tank or the batteries) and others are scaled on its mass (such as the engine, using a representative power-to-curb mass ratio), and because the energy consumption of a vehicle is itself affected by its driving mass, those are defined iteratively until their values converge (i.e., until they do not change significantly between two iterations).

2.2.2 Sizing of energy storage components

The sizing of some components also depends on the required range autonomy of the vehicle – the distance it must be able to drive on a single tank filling/battery charging. This is particularly relevant for BEV trucks. The tank-to-wheel energy consumption (see next section) and the range autonomy are determinant to the battery capacity. The mass of the batteries is primarily determined by the energy density of the cells. As the driving range increases, the batteries "eat away" some of the payload capacity. If the vehicle curb mass reaches the vehicle gross mass, the payload capacity becomes inexistent and the vehicle cannot be considered further. For example, Figure *1* shows the available payload function of the required range autonomy for a 40-ton BEV truck, from 2020 to 2050. Expected improvement of the energy density of battery cells over time, going from 0.2 kWh/kg today [29], and up to 0.5 kWh/kg in 2050 [30] (equivalent to 0.12 and 0.35 kWh/kg of battery system, respectively), is the primary enabler for increasing the available payload given a required range autonomy – as well as other improvements that indirectly reduce the curb mass. By default, the required range autonomies of 150, 400 and 800 km are respectively set for the three driving cycles available, namely "Urban delivery", "Regional delivery" and "Long haul".

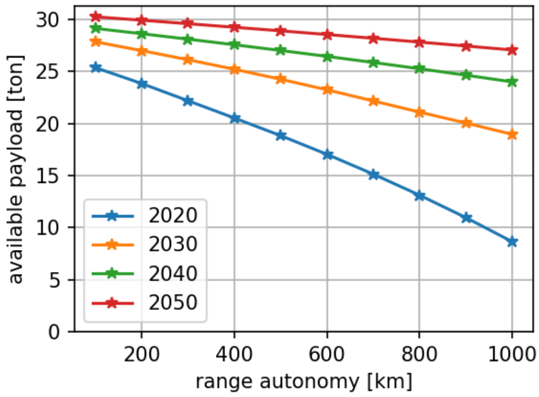


Figure 1 Available payload as a function of the range autonomy for a 40-ton BEV truck.

2.2.3 Fuel and electricity supply

Over twelve different fuel pathways are available to power the vehicles. They include traditional fuels like diesel, natural gas and biofuels, but also fuels from emerging technologies like hydrogen from reforming of bio-methane or wood gasification with HPR or entrained flow gasifier (with and without carbon capture and storage)[31,32] or synthetic methane from hydrogen and carbon dioxide from direct air capture[33]. The fuels are listed in Table 3 of the SI. Custom fuel blends can be specified. Some fuel blends can contain a significant amount of alternative fuel, which characteristics can also affect the required energy storage capacity. For example, an extensive use of biodiesel, which has a lower net calorific value than conventional diesel, leads to filling the truck tank with a larger amount of fuel to maintain the required range autonomy. This increases the driving mass of the vehicle and its energy consumption.

For vehicles that require electricity directly (e.g., BEV, for battery charging) or indirectly (e.g., FCEV, to supply hydrogen via electrolysis), the electricity mix is either user-defined or calculated based on the country of use. The former option allows to conduct analyses using a specific electricity technology (e.g., wind power only). In the second option, the electricity mix used is a result of the averaged projected electricity mixes over the period of use of the vehicle (e.g., from 2020 to 2032, if the vehicle is first used in 2020 and has an expected lifetime of 12 years) in the specified country. This tends to result in “greener” electricity mixes than simply using the electricity mix of the first year of use. Indeed, projected national electricity grid developments (often synonymous with expanding renewable energy sources) are accounted for. Further explanation on how such mixes are calculated is available in the section 2.2.1 of the SI. *carculator_truck* includes gross electricity mixes for ninety countries from 2000 to 2050. Projections for European, African and remaining countries are from [34], [35] and [36], respectively.

2.2.4 Tank-to-wheel energy consumption

When a preliminary value is given to the driving mass, the different resistances the vehicle must overcome are calculated for each second of the driving cycle. As their names suggest, the three driving cycles available represent different types of applications. They define the target speed levels for every second of driving and are extracted from the VECTO software [37]. The actual speed profiles considering the vehicles specifications (i.e., driving mass, engine power, gearbox, etc.) for the first hundred seconds of the “Long haul” driving cycle are depicted in Figure *2*, based on a simulation using the VECTO software. Intuitively, heavier vehicles need more time to reach the target speed. There is however an interesting aspect also highlighted: the 40-ton and 60-ton vehicles do not simply have time to reach the target speed as they already need to decelerate to come to a stop by second 90 and 100, respectively. Lighter vehicles, on the other end, tend to have steeper accelerations and start decelerating (or braking) later comparatively. This trend is observed on most of the driving cycle duration and mostly on driving cycles with frequent stops. It results in heavier vehicles reaching, on average, lower speed levels with narrower fluctuations in speed levels than lighter vehicles – which is reflected on their energy consumption.

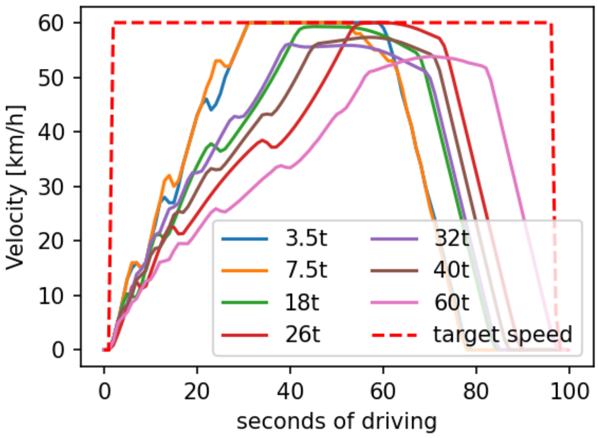


Figure 2 Speed profiles per second of driving for the first one hundred seconds of the "Long haul" driving cycle.

For each second of the driving cycle, the various types of resistance encountered by the vehicles are calculated. This allows to obtain the amount of power that should be transmitted at the wheels. This is then compared to the results obtained from the VECTO simulations, using similar trucks specifications. Finally, the tank-to-wheel energy requirement should be calculated. Here, VECTO uses a complex model considering gearbox and engine torque maps, where the efficiency of those components varies according to the gear used, but also the speed and torque to deliver. While replicating such model would be outside of the scope of this study, a simpler approach is adopted for ICEV-d trucks. The efficiency of the engine and the transmission is approximated based on the relative power load required. This reflects an increase in efficiency for both the engine and the transmission as the drivetrain operates closer to its maximum rated power output. It also allows to consider the effect of engine downsizing. The details of such modeling and the calibration and validation against VECTO simulations are detailed in the Section 2.3 of the SI. The tank-to-wheel energy consumption calculated by *carculator_truck* and VECTO with ICEV-d trucks of similar specifications do not differ by more than 1% on all driving cycles. Hybrid diesel vehicles (i.e., HEV-d and PHEV-d), for which part of the combustion engine power has been re-allocated to an electric motor, reach higher efficiency levels as the engine operates more often at relatively higher power load. They also have the advantage of being able to recuperate a part of the energy spent braking or decelerating thanks to their electric motor, if the driving cycle chosen permits it.

VECTO does not come with engine maps for CNG engines. Hence, current efficiencies for CNG engines are set to be 19% lower than what is obtained from the calibration of ICEV-d trucks, corresponding to the performance of a spark-ignition CNG engine, according to [38]. By 2030, the engine is assumed to be of compression-ignition type to achieve better performances. It reflects the use of a dual CNG-diesel fuel injection system, which reduces the relative difference in thermal efficiency compared to a diesel engine to 14%, as reported by [38]. After 2030, the efficiency of the CNG engine converges with that of a diesel engine to reach equivalent performances by 2050, as also suggested by [38].

In the absence of electric motor specifications in VECTO, such calibration could neither be extended to BEV or FCEV powertrains. Instead, literature data from electric and fuel cell vehicles – see Tables 9 and 10 of the SI – is used to approximate the engine and transmission efficiency rates of those powertrains. Like HEV-d and PHEV-d, FCEV and BEV trucks can recuperate a fraction of the braking energy during deceleration or downhill sections of the driving cycle.

In a comparison between trucks from 1994 and 2015, Transport & Environment [39] demonstrates that the fuel efficiency of North American and European trucks over that period remained unchanged. Engine efficiencies did not markedly increase due to additional emissions-limiting measures which led manufacturers to increase the engine power, and thereby the fuel consumption. The curb mass of the vehicles also did not decrease. In fact, it seems to have slightly increased due to additional safety equipment. Default efficiency values reflect that past development.

As for the projected developments over the period 2021-2050 for diesel and compressed natural gas-based powertrains, CO_2 targets for trucks as implemented by the European Union [40] are used by default. These targets correspond to a 15% and 30% reduction of CO_2 exhaust emissions by 2025 and 2030 respectively, compared to 2020, on a fleet basis. While it is not entirely correct to use fleet-based targets on single vehicle technologies, it is unlikely that “zero emissions” vehicles will represent a significant share of any fleet by 2030. Hence, diesel and compressed natural gas trucks will still have to substantially reduce their exhaust emissions down by a factor close to the mentioned target. In their 2018 report, ICCT forecasts a number of energy efficiency improvements for diesel trucks at the engine level by 2030, including waste heat recovery, engine downsizing, etc., to comply with future regulations on energy efficiency [41]. In *carculator_truck*, a similar approach is used by increasingly hybridizing the powertrain to reduce the size of the combustion engine, as it is being compensated by an electric motor. It results in additional recuperated energy – only if the driving cycle permits it – and the combustion engine to operate less often, but at a higher power load, where its thermal efficiency is higher. *carculator_truck* iteratively increases the hybridization rate of the powertrains until they comply with the defined emission reduction targets. If the driving cycle does not allow for substantial energy recuperation, energy efficiency gains through the hybridization of the powertrain will be limited. If the energy efficiency gains are insufficient, the vehicles are declared “non-compliant”, but their results are still calculated. In the Results section, non-compliant vehicles are marked with a star (*). The user of *carculator_truck* has the possibility to change these emission targets to reflect other policies.

2.2.5 Fuel-related exhaust emissions

Carbon dioxide emissions that result from the combustion of liquid and gaseous fuels are calculated based on the tank-to-wheel energy consumption of the vehicle, the net calorific value of the fuel blend as well as its CO_2 emission factor. The combustion of biofuels and synthetic fuels also leads to CO_2 emissions. They are though compensated by the CO_2 uptake during the fuel preparation (i.e., biomass growth for biofuels, or direct air capture for synthetic fuels). Several heavy metals are also emitted because of burning conventional diesel and are calculated using the emission factors expressed in kg/kg diesel as reported in [42].

Sulfur dioxide emissions are also calculated based on fuel consumption. A varying sulfur content in the diesel fuel is considered across geographies and time. Time series for the sulfur content in fuels for a limited number of countries (i.e., Austria, Switzerland, France, Germany and Sweden) are extracted from the HBEFA 4.1 database [43], while [44] provides current sulfur content for over 190 other countries. Additionally, European countries for which specific time series are not available are assumed to follow the European regulations on sulfur content in on-road diesel fuel (from 2,000 ppm in 1994 down to 10 ppm today). Finally, it is assumed that countries that have a sulfur content above 50 ppm today will converge towards a concentration of 50 ppm by 2050, as recent developments seem to suggest [45]. Figure 7 of the SI shows a map of sulfur concentration values in on-road diesel fuel considered in 2020.

Finally, pump-to-tank leaks when filling with gaseous fuels are also considered. They are accounted for as a fraction of the fuel input, with a median value of 0.4%, as reported by [38], being directly emitted as methane.

2.2.6 Emissions of regulated substances

Several other emissions, which also correlate with the fuel consumption, occur during the use phase of the vehicle. It is the case of hot pollutants such as CO, NO_x, CH_4, etc. These substances, which are regulated by European emission standards, are calculated based on the fuel consumption of the vehicle, for each second of the driving cycle. A linear regression fit is modelled across emissions factors supplied by the HBEFA 4.1 database [46], for different fuel consumption levels, EURO emission standards and traffic situations. Additionally, a few compounds are derived as a fraction of total NMVOC emissions, such as benzene, toluene, xylene, formaldehyde, acetaldehyde, etc. [42]. The correlation used between emissions factors and fuel consumption for different emission standards and fuel types is depicted in section 2.5 of the SI. Emission factors for future ICEV-d and ICEV-g vehicles are not known and are assumed to remain at the level of 2020 (i.e., EURO VI). Potential hybridization of their powertrains in the future, where an electric motor assists the internal combustion engine, helps reduce these emissions.

Furthermore, different environments of use are identified within each driving cycle to differentiate calculated emissions by compartment of emissions, namely urban, suburban and rural. The respective shares of emissions by compartment for each driving cycle are specified in Table 7 of section 2.5 of the SI. Distinct characterization factors – depending on the Life Cycle Impact Assessment (LCIA) method applied are used for assessing their impacts regarding. It is the case, for example, with impacts on the human respiratory system, as different characterization factors for emissions are used for urban, suburban and rural compartments, reflecting differences in population density.

2.2.7 Non-exhaust emissions

Several non-exhaust emissions are also considered, namely abrasion particles from tires, brakes and road wear, but also noise emissions, from tire rolling and propulsion.

2.2.7.1 Abrasion particles

Based on the Tier-2 methodology presented in [47], brakes, tires and road wear emissions are calculated considering the driving cycle, number of axles and the load factor of the vehicle. Additionally, based on the evaluation report of the American Fuel Cell Bus project [48], where the maintenance costs of 5 CNG buses where compared to those of 4 FCEV buses over 18 months in 2011, the cost in brake part replacement for FCEV buses were only 10% of that of CNG trucks. Such difference is also used by default in this study to adjust brake wear particle emissions for trucks equipped with an electric motor – the user can however easily modify this assumption.

2.2.7.2 Noise emissions

Noise emissions are calculated according to the CNOSSOS model [49]. First, sound power, in A-weighted decibels, is calculated for each second of the driving cycle, with tire rolling and propulsion noise coefficients for medium and heavy-duty vehicles and correction coefficients for electric powertrains [50]. Propulsion noise usually dominates up to 50 km/h. Above that speed, rolling noise becomes predominant, regardless of the powertrain.

The sum of noise power over time divided by the distance of the driving cycle results in noise energy (joules) per km driven, which are then converted in Person-Pascal-second. As with hot pollutant emissions, different emission compartments are identified for each driving cycle (i.e., urban, suburban and rural), as environment-specific characterization factors (from Person-Pascal-second to Disability-Adjusted Life Year) are used to assess the impact of noise energy on human health, according to [51].

2.3 Material and energy inventory

The vehicle components, their size and mass and the vehicle energy consumption are part of the foreground aspect of the model. The supply of energy, materials and services needed to support the different life cycle phases of the vehicle are part of the background aspect of the model. Foreground and background aspects of the model are approached differently.

2.3.1 Foreground inventory

Table 8 of the SI lists the different component datasets used as well as their sources. Most of these components rely on the supply of material, energy and services, provided by the background inventory databases presented in the next section.

2.3.2 Background inventory

Foreground inventories link to background inventory databases. Background inventory databases are created using *premise* [52], a Python library which integrates the outputs of the global Integrated Assessment Model REMIND [53] into the LCA database ecoinvent v.3.7.1 (system model “allocation, cut-off by classification”) [54]. Variants of the ecoinvent database have been created for the years 2000 to 2050, by 10-year steps, under different REMIND energy scenarios defined by Shared Socioeconomic Pathways (SSP). Across time within a same energy scenario, the energy efficiency and emissions of power plants in the database are adjusted, as well as electricity supply markets. Across energy scenarios, the presence of emerging technologies, notably Carbon Capture and Storage (CCS), is introduced to varying degrees. Variants of the ecoinvent database available in *carculator_truck* are created based on different energy scenarios. A description of available energy scenarios available in the premise library is available on the code repository [55]. Results displayed in the next section use the *baseline* energy scenario of “SSP2” – the reader can refer to [56] for more information on SSP. This is a conservative scenario that projects cumulative GHG emissions to reach 5,000 Gt globally by 2100 (corresponding to an increase in atmospheric temperature of 4 degrees Celsius). Modifications at the power generation level and its supplying markets affect all the activities in the database and is of great relevance for the supply of electricity, but also steel, aluminum and other energy-intensive materials for prospective analysis.

2.3.3 Impact assessment

Foreground and background inventories values are stored in a three-dimension array *A*, which dimensions are supplying activities, consuming activities and iterations (which length equals 1 in the case of a simple analysis, or the number of iterations in the case of a Monte Carlo or sensitivity analysis). The total requirements in terms of material and energy from each supplying activities, represented by a scaling factor *x*, are obtained given a demand vector *f* (i.e., 1 ton-km from a specific vehicle) so that $Ax = f$.

Another multi-dimensional array *B*, which contains pre-calculated values of ecoinvent activities for different mid- and endpoint indicators for different years and REMIND energy scenarios, is multiplied with *x* to obtain the environmental impacts associated to the functional unit.

The available mid- and endpoint impact assessment indicators are part of Recipe 2008 [57] as well as ILCD 2018 [58]. The library also allows to export inventories in different formats, to be reused in LCA software such as Brightway2 [59] and Simapro [60] where other indicators are available.

For this analysis, results are shown using the Global Warming Potential indicator based on IPCC's 2013 characterization factors [61], expressed in kg CO_2-eq. with a time horizon of 100 years. As mentioned earlier, the *baseline* energy scenario of the Shared Socioeconomic Pathway SSP2 is used for projections.

3 Results

This section presents comparative results across powertrains, size classes and applications. While *carculator_truck* has a wide catalogue of impact assessment indicators and energy scenarios, the results presented here use a baseline energy scenario with the Global Warming Potential indicator representing impacts on climate change. Additionally, the various calculated trucks specifications (i.e., loading factor, tank-to-wheel efficiency, fuel consumption, battery replacements) the results are based upon, are detailed in sections 4.1 to 4.3 of the SI document.

3.1 Comparison across powertrains and duty cycles

Figure 3 compares the GHG emissions of a 40-ton vehicle across powertrain types, years, range autonomies, and driving cycles per vehicle-kilometer (without cargo) and ton-kilometer (assuming an equal load factor). Similar figures for other gross weight categories are included in the SI – see Figures 12-13 of the SI. Vehicles for the years 2000, 2010 and 2040 as well as hybrid and plugin-hybrid vehicles are left out to avoid displaying too much information. This analysis uses the yearly mileage-weighted electricity consumption mix in the European Union given by the baseline REMIND projection for SSP2 over the lifetime of the trucks (e.g., from 2020 to 2032 for vehicles of the year 2020, from 2030 to 2042 for vehicles of the year 2030, etc.) to charge batteries and produce hydrogen via electrolysis. For vehicles produced in 2020 and operating until 2032 (i.e., the assumed lifetime of a 40-ton truck), it consists of 10% hydro power, 15% nuclear power, 17% natural gas power, 25% from waste incineration, 5% photovoltaic power, 10% wind power, 3% biomass-based power, 13% coal-based power and 1% from fuel oil, for an overall GHG intensity of 344 g CO_2-eq./kWh. For reference, the GHG intensity of European electricity is currently 387 g CO_2-eq./kWh [54]. The GHG intensity of the electricity used for battery charging or hydrogen production for the vehicles produced in 2030, 2040 and 2050 is 285, 239 and 209 g CO_2-eq./kWh, respectively.

The ranking of performances between the vehicle-km basis and the ton-km basis is similar with the notable exception of the BEV truck, for which the limited carrying capacity in 2020 due to large batteries to ensure a high range autonomy penalizes its performance on a ton-km basis. Across driving cycles, direct exhaust emissions per ton-km of loaded ICE vehicles in the context of urban use (the reader should refer to the "Urban delivery" driving cycle on the right panel of Figure 3) seems higher than in a context of long hauling. This comes from a higher fuel consumption due to steeper accelerations and more frequent stops for deliveries, as opposed to higher but more constant speed levels for the "Long haul" driving cycle. The difference for empty vehicles on a vehicle-km basis is also present, but less pronounced. This is an opportunity for BEV trucks which, thanks a superior tank-to-wheel efficiency, should perform better than other powertrains provided the range autonomy required is limited. BEV trucks appear to become a viable and competing option in terms of life cycle GHG emissions both on a vehicle-km and ton-km basis as soon as 2020 for such short-distance use. On the other hand, in a long-hauling scenario where a larger range autonomy is required, there is a higher impact associated to energy storage for the BEV option and the effect of its mass on the motive energy required (and the amount required upstream the energy chain) is important – because of this, BEV trucks do not manage to be among the preferred options for long-distance trips before 2040. This is confirmed by the review of current prototypes and early commercial BEV models (see Figure 10.c of the SI), which seem specifically conceived for urban use with a low range autonomy. ICEV-d trucks, despite reducing their on-road GHG emission by 15% between 2020 and 2030, do not manage to keep up with fully electrified powertrains on the long-term (i.e., after 2030). They also do not manage to reach the short-term emission reduction targets of 30% in 2030 and 2040 on the “Regional delivery” and “Long haul” driving cycles (vehicles marked with a star in Figure 3), while they do with the “Urban delivery” driving cycle. This is because the energy saved from energy recuperation through the hybridization of the powertrain remains limited when the driving cycle is dominated by sections of highway driving. This is shown by the gray vertical lines at the level of ICE vehicles on the left panel of Figure 3. They represent the sum of emissions without hybridization of powertrains – which is otherwise needed to try to reach the emissions reduction targets. Despite a lower CO_2 emission factor for compressed natural gas, *current* ICEV-g trucks are penalized by a relatively inefficient spark ignition engine together with methane emissions along the fuel supply chain. By 2030, the adoption of compression ignition engines should help ICEV-g trucks to align with the GHG emissions of ICEV-d trucks. However, it is not before the performances of gas engines fully align with those of diesel engines in 2050 that ICEV-g trucks will offer a clear benefit in terms of GHG emissions. Finally, FCEV trucks, running on hydrogen produced by electrolysis, have the advantage of having an electrified powertrain with a reduced mass for energy storage relative to BEV trucks. Yet, in this scenario, they do not manage to outcompete ICEV-d and ICEV-g trucks due to their relatively inefficient energy chain combined with an electricity still too GHG-intensive on average by 2050 (i.e., 209 g CO_2-eq./kWh). However, Figure 5.a of section 3.3 shows that this situation can change should the FCEV trucks use hydrogen generated with low-carbon electricity.

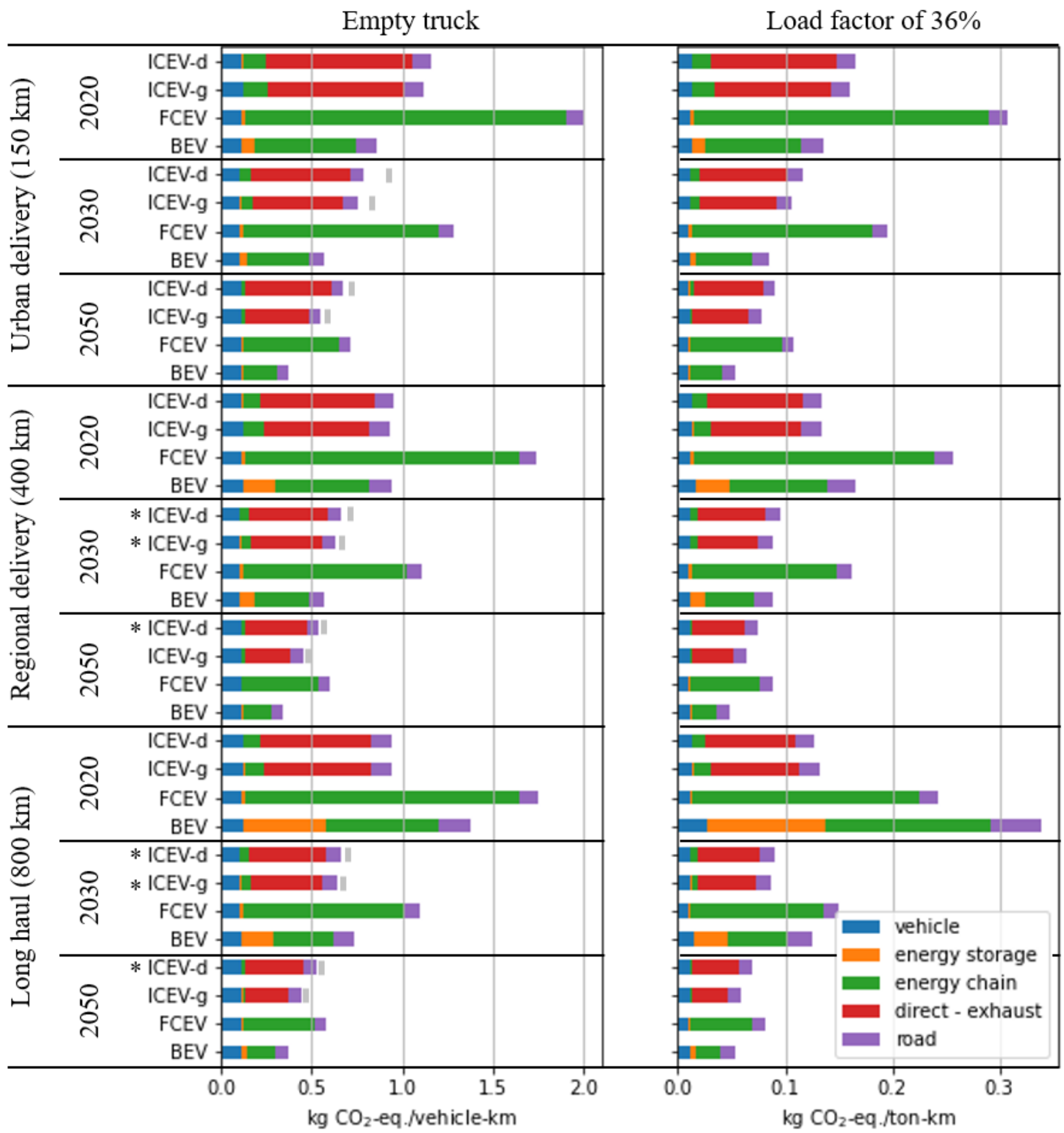


Figure 3 Per vehicle-km (left panel) and per ton-km (right panel) GHG emissions comparison across powertrains and years for 40-ton trucks, for different range autonomies and driving cycles. Fuel for ICEV-g: compressed natural gas. Fuel for FCEV: electrolysis-based hydrogen. * Vehicles marked with a star (*) do not manage to comply with the CO_2 emissions reduction targets (-15% by 2025, -30% by 2030) despite energy efficiency improvements. Average European electricity is used for battery charging and hydrogen production. Vertical gray lines at the level of ICE vehicles represent their emissions without powertrain hybridization.

3.2 Importance of size class, driving range and load factor

Figure *4* shows the influence of the energy density of battery cells on the payload capacity of a 40-ton BEV truck as a function of the range autonomy and the associated life cycle GHG emissions per ton-km calculated with average load factors. As the range autonomy increases, so does the battery mass. This leads to impacts evolving in a more than proportional manner as the overall impacts are normalized by the cargo mass transported, which itself converges towards zero (as it is increasingly being replaced by the battery mass). While this effect has a very substantial impact on the results today with the current battery technology, the expected improvements are significant by 2050. However, they are only realized if the energy density of battery cells does reach 0.5 kWh/kg cell by 2050. As of today, BEV trucks do not seem to be suitable for long-hauling operations. Finally, Figure 14 in the SI shows the relation between gross weight category and GHG emissions per ton-km for a 40-ton ICEV-d truck. Economies of scale are observed despite lower size vehicles benefitting from a higher load factor. This is easily explained by the decreasing payload-to-curb mass ratio, calculated as ranging from 1.06 ton of curb mass per ton of payload for a 3.5-ton truck, down to 0.57 for a 60-ton truck.

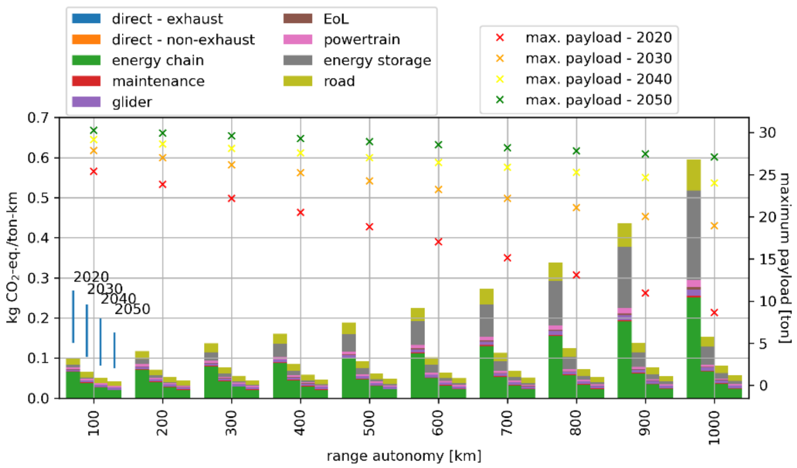
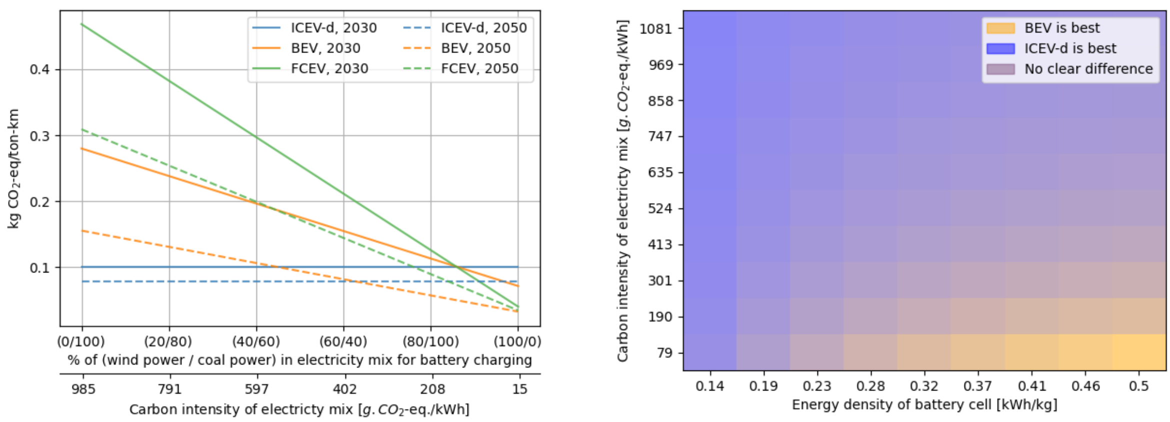


Figure 4 GHG emissions per ton-km as a function of range autonomy for a 40-ton battery electric truck (calculated with average load factors and the European electricity mix for battery charging).

3.3 Diesel, batteries, or fuel cells?

This section identifies determining parameters that can promote a certain powertrain technology over another one. Figure *5*.a shows for which minimum GHG intensity level of the electricity grid 40-ton BEV and FCEV trucks can compete with equivalent ICEV-d trucks on long-haul trips. In 2030, BEV and FCEV trucks can compete with their diesel counterpart when the GHG intensity of the electricity is below 170 g CO_2-eq./kWh. In 2050, as drivetrains improve (i.e., ICEV-d drivetrains are increasingly assisted with an electric motor, the battery weight of BEV decreases and the efficiency of fuel cell systems on FCEV trucks improves), the GHG intensity of the electricity needs to be below 400 g CO_2-eq./kWh for BEV trucks to start outcompeting ICEV-d trucks. For FCEV trucks, the break-even point is around 200 g CO_2-eq./kWh. This shows that, as long as coal and natural gas power plants contribute substantially to the electricity mix, the likelihood of electric powertrains to compete with ICEV-d trucks in terms of GHG emissions on long haul applications is low. A similar analysis, but this time per vehicle-km without load, is shown in Figure 15 of the SI. It shows that the comparison of BEV vs. ICEV-d very much depends on whether it is performed using average load factors as in Figure 5.a, or assuming equal load as in Figure 15 of the SI.

As the GHG intensity of the electricity used for battery charging and the size of the battery are two important factors determining the carbon footprint of BEV trucks, Figure 5.b shows the ratio of life cycle GHG emissions for BEV trucks over those of ICEV-d trucks for long haul operations (800 km of range autonomy), for a given combination of GHG intensity of electricity and energy density of battery cells. As this ratio tends to the favor of BEV trucks, the color of the cell tends to yellow and vice-versa. BEV trucks seem to provide an advantage over ICEV-d trucks with the condition of a minimum energy density of the battery cells of 0.3 kWh/kg combined with a maximum GHG intensity of the electricity of 150-170 g CO_2-eq./kWh.

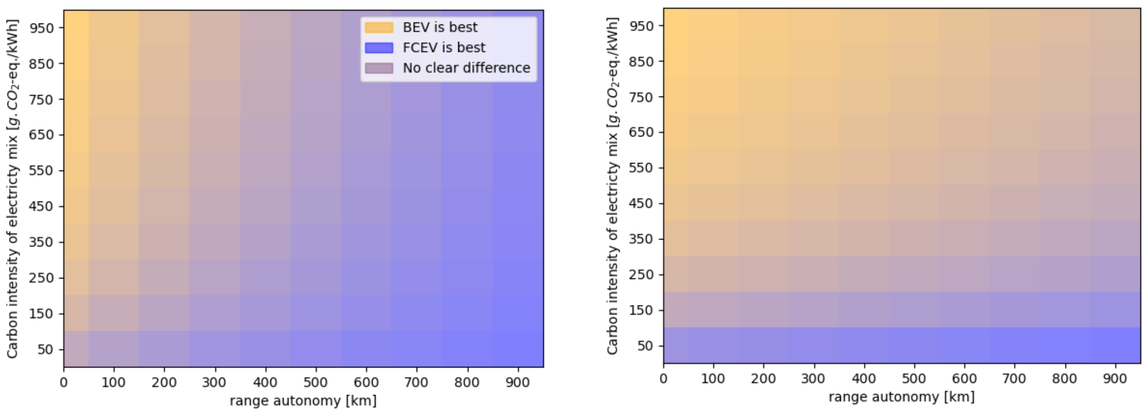


a) GHG emissions per ton-km as a function of the GHG intensity of electricity, with a range autonomy of 800 km: comparison between a 40-ton BEV, FCEV and ICEV-d truck.

b) GHG emissions per ton-km as a function of the GHG intensity of electricity and energy density of battery cells, with a range autonomy of 800 km: comparison between a 40-ton BEV and ICEV-d truck in 2030.

Figure 5 Comparison between ICEV-d and BEV 40-ton trucks for long haul applications, calculated with average load factors

Regarding the comparison between BEV and FCEV trucks, besides developments in battery technology (i.e., battery cell energy density, energy requirement for the manufacture of battery cells, etc.), improvements of the fuel cell stacks in FCEV trucks are also considered: an energy efficiency of 50% in 2020 (calibrated based on specifications from FCEV trucks manufacturers – see section 3.3 of the SI), to 58% in 2050[5], an increase in the power area density of the cells from 0.9 W/cm^2 in 2020 to 1.2 W/cm^2 in 2050[11] (thereby reducing the platinum loading from 0.15 to 0.11 g Pt/kW) as well as a small reduction of the energy needed to support the balance of plant. However, no improvement in terms of efficiency has been considered regarding the production of hydrogen via electrolysis, as suggest by [62]. Figure *6* shows the ratio of life cycle GHG emissions of 40-ton BEV trucks over those of equivalent FCEV trucks, given the GHG intensity of the electricity and the required range autonomy, for 2020 and 2050. In 2020, FCEV trucks have an advantage over BEV trucks for long haul usage, and this regardless of how carbon-intensive the electricity is. It still holds true in 2050, despite significant expected improvements of the battery size for BEV trucks, but only if the GHG intensity of electricity is very low (i.e., below 100 g of CO_2-eq./kWh). As the electricity becomes more carbon-intensive, the life cycle GHG emissions of BEV trucks get closer to those of FCEV trucks when the required range autonomy is high (see top right corner of Figure *6*.b). On the other hand, BEV trucks show lower life cycle GHG emissions when the required range autonomy is low in 2020 and 2050. This superiority is ascertained as the electricity becomes more carbon-intensive – however, above 400 g CO_2-eq./kWh, ICEV-d trucks are a better option in 2050, as seen in Figure *5*.a.



a) In 2020

b) In 2050

Figure 6 Comparison of GHG emissions per ton-km between BEV and FCEV (hydrogen from electrolysis) function of electricity GHG intensity and range autonomy, calculated with average load factors

3.4 Beyond powertrains: the role of energy pathways

It seems however important to nuance the results, as potential future improvement may not only come from efficiency gains at the vehicle level, but could also be achieved through the development of emerging fuel technologies. Figure 7 shows that the life cycle GHG emissions of a 40-ton diesel truck in 2050 using conventional diesel can be roughly halved using low-carbon electricity directly for BEV or indirectly for producing hydrogen used by FCEV trucks or synthetic diesel for ICEV trucks, as well as waste biomass-based biofuels. In this comparison, the GHG intensity considered for the European electricity mix in 2050 is 209 g CO_2-eq./kWh, according to the baseline projection for SSP2. Using CCS represents an option for hydrogen production from natural gas and biomass. Life cycle GHG emissions close to (or even below) zero are possible when using biomass-based hydrogen production with CCS, since these fuel production pathways exhibit negative GHG emissions due to permanent removal of CO_2 from the atmosphere [31,32].

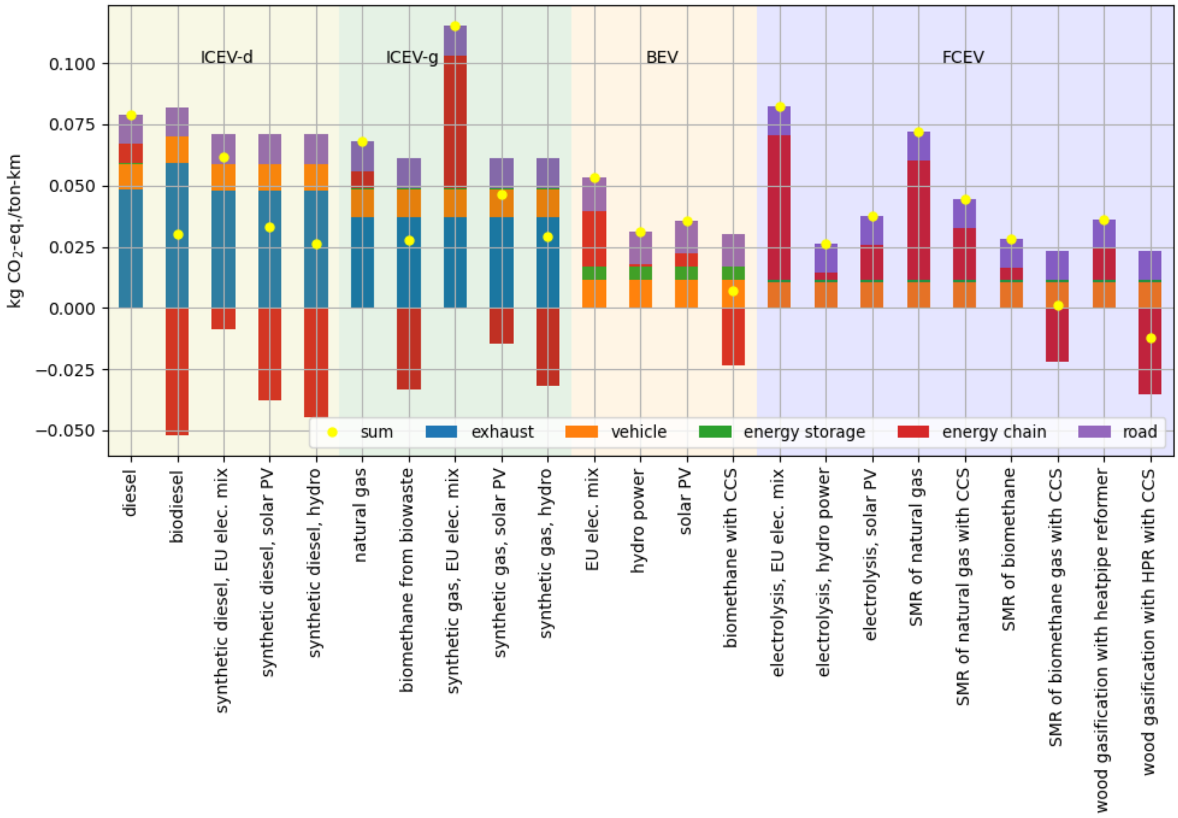


Figure 7 Per ton-km GHG emission of a 40-ton truck across different fuel pathways in 2050 (“Long haul” driving cycle, 800 km of range autonomy, equal load factors). The GHG intensity of the European electricity mix in 2050 is 209 g CO_2/kWh.

4 Discussion

Despite a comprehensive and novel approach, several limitations in this work must be acknowledged and addressed in the future:

- While the vehicle model for conventional powertrains could be calibrated on VECTO simulation results and validated against a large dataset on diesel trucks, such data are lacking for both BEV and FCEV trucks, and are limited for compressed natural gas trucks. Therefore, associated uncertainties are higher. Specifically, it should be stressed that electric powertrains are modeled with a constant engine and drivetrain efficiency: although their motive energy requirement differs across driving cycles, the efficiency at which energy is transmitted from the electric motor to the wheels is insensitive of the operating load.
- Thanks to *premise*, this prospective LCA considers the expected developments in the background system for the electricity and cement sector. An analysis should be run with an ulterior version of *premise* to include expected developments in heat supply and other energy-intensive industrial sectors, but also with different narratives.
- While *carculator_truck* allows to quantify a complete set of midpoint indicators, the current analysis is limited to impacts on climate change. Further environmental issues must be addressed, ideally applying regionalized impact assessment methods to capture benefits of electric powertrains regarding human health impacts in densely populated areas.

Limitations aside, electric powertrains seem to be the most effective option to reduce impacts on climate change at large scale by 2050 – provided a "decarbonized" electricity supply and acknowledging limited supply potentials for renewable power generation in Europe. More specifically, battery electric powertrains would yield most benefits in an urban context, where energy storage requirement is low and where the electric motor would preserve a good efficiency despite transient loads. This relies, however, on expected improvements that yet need to be realized, especially in terms of battery technological improvements. Additionally, these improvements need to happen while keeping costs low, as they need to compete against mature and well-developed diesel and natural gas-based powertrains, which, in the meanwhile, could reduce their exhaust emissions by 50% through hybridization combined with biofuels and electricity-based synthetic fuels given a very low GHG intensity of the electricity. Therefore, much of the potential of these emerging technologies applied to trucks is yet to be proven. Furthermore, the GHG intensity of electricity is not guaranteed to be reducing at the expected pace or evenly across the globe. Fuel cell electric powertrains would on the other end become a key technology for long haul transportation, where the payload capacity is prioritized. They do not need to rely entirely on hydrogen from electrolysis (i.e., low-carbon electricity), but can also use other low-carbon fuel production pathways, namely natural gas reforming with CCS and biomass feedstock (with and without CCS). In the context of biomass-based fuels, resource limitations need to be considered.

Finally, the environmental assessment presented here should ideally be accompanied by a cost assessment. Emerging vehicle and fuel technologies must compete with mature and optimized technologies which probably have lower levelized costs of ownership. In fact, hybridizing the powertrains of diesel and natural gas-powered trucks, combined with the development of bio- and synthetic fuels may well provide significant reductions in terms of life-cycle emissions without bearing the complexity and cost of a fully electrified powertrain.

Supplementary information

Complementary description of the method, variable inputs, results and commercial truck models used for validation are supplied in the supporting information (SI) document, which is available online.

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Authors information

Romain Sacchi joined the Technology Assessment group at the Paul Scherrer Institute in June 2019 as a Postdoctoral Researcher, to contribute within the field of Life Cycle Assessment (LCA) applied to future mobility technologies. Christian Bauer is working in the Technology Assessment group since 2004. His main research areas are Life Cycle Assessment and sustainability assessment of current and future electricity and heat supply technologies as well as conventional and innovative transport systems. Brian Cox is a scientific consultant at INFRAS, where he works on transport emissions modelling and sustainable mobility.

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