Life Cycle Impacts of electrified vehicles considering use behavior and battery aging

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Abstract

This study assesses in depth the environmental impacts of electrified vehicles considering Plug-in Hybrid Electric Vehicles (PHEVs) as the most complex case, emphasizing the role of driving behavior, charging habits, and battery aging. By modeling realistic daily and annual mileage patterns, the study captures the variability in PHEV use and its significant effect on emissions. A comprehensive Life Cycle Assessment compares PHEVs, Battery Electric Vehicles, Hybrid Electric Vehicles, and Conventional Vehicles, using electricity mixes from France and Germany. The results show that electrifying vehicles allows consistent reductions for certain impact categories, as Global Warning Potential. However, it is strongly dependent on the electricity mix and electrified vehicles present higher values for certain other impact categories. The last part studies the influence of increasing battery size related to battery aging. Larger batteries may slightly extend vehicle lifespan, but their added production impacts often outweigh environmental gains.

Keywords: Life cycle assessment, Passenger cars, Electrified vehicles, Battery aging, Use case scenarios

1. Introduction

As we shift towards sustainability, electrifying transportation is essential for mitigating climate change. Despite global and EU initiatives promoting this shift, a comprehensive understanding of the environmental impacts of electrified vehicles is still lacking. The production of batteries, a critical yet ecologically challenging stage, highlights the need for a comprehensive approach. Employing Life Cycle Assessment (LCA) allows us to study the full environmental consequences from production to disposal, ensuring that our transition to electrified vehicles aligns with broader sustainability objectives Das et al. (2024).

Numerous studies have investigated the LCA of various electrified vehicles, including battery electric vehicles (BEV), hybrid electric vehicles (HEV), and plug-in hybrid electric vehicles (PHEV), as well as different types of batteries. A thorough review of the literature has been conducted to gain a comprehensive understanding of pre-existing research and to enable a comparative analysis of the findings presented in this study.

For instance, Helms et al. (2015) analyzed compact vehicles in Germany, examining PHEVs with electric ranges of 20 km and 50 km over 168,000 km. Xiong et al. (2019) extended this analysis to PHEVs with longer electric ranges of 80 km and 100 km, covering 160,000 km and 120,000 km, respectively. Meanwhile, other studies, such as Bouter et al. (2020), focused on different powertrain configurations in cars and buses within the French context, considering a lifetime mileage of 150,000 km. Yang et al. (2021) and Xiong et al. (2021) applied similar mileage values to passenger vehicles in China, assessing internal combustion engine vehicles (ICEVs), PHEVs, and BEVs to evaluate carbon dioxide (CO_2)-Eq and air pollutant emissions. Additionally, Öivind Andersson and Börjesson (2021) examined the greenhouse gas impact of hybrid and battery electric vehicles over 200,000 km using renewable fuels in a Swedish context.

In evaluating emissions, studies employed various modeling approaches, emphasizing either fixed emission parameters or real-world data integration. For example, Xiong et al. (2019) and Kannangara et al. (2021) used fixed emission values in their analyses. Conversely, Xiong et al. (2019) and Szilágyi and Bereczky (2018) incorporated real-world driving data to calculate fuel consumption. More advanced dynamic simulation models were applied in studies by Helms et al. (2015), who utilized the TREMOD model, and Bouter et al. (2020), who employed IFPEN vehicle simulators. Yang et al. (2021) relied on the GREET model in their assessment of emissions in China, while Öivind Andersson and Börjesson (2021) integrated WLTP procedures with data from the Swedish Energy Agency.

Several studies presented data regarding the global warming potential (GWP) in CO_2 equivalents Shui et al. (2024). However, since life cycle assessment (LCA) aims to provide a comprehensive understanding of environmental burdens, it should consider multiple impact categories beyond climate change. For instance, Lombardi et al. (2017), Szilágyi and Bereczky (2018), and Xiong et al. (2019) expanded their analyses to include categories such as acidification, eutrophication, or resource depletion, though quantitative results were often only illustrated in figures rather than reported as explicit values. Despite these broader considerations, most studies continued to emphasize CO_2-Eq-related emissions, reflecting a predominant focus on global warming potential, sometimes also linked to economic or energy performance assessments Xu et al. (2023).

One significant limitation in these studies is the absence of a robust battery aging model to estimate battery lifespan based on vehicle usage. Instead, many rely on constant values derived from previous research. Peters et al. (2017) and Nordelöf et al. (2014) highlighted the environmental and financial risks associated with battery replacements, which could render older electric vehicles economically unviable and environmentally burdensome. This lack of aging models is compounded by the reliance on assumed material compositions or estimates from the literature, highlighting a broader issue of lack of primary data in these analyses. For instance, Helms et al. (2015) based their material composition on primary data from Volkswagen, studies, and assumptions. Yang et al. (2021) assumed their vehicle to be similar to a Toyota Corolla, while Lombardi et al. (2017) used data based on a Chevrolet Malibu, which in comparison to all other previously mentioned research is no compact vehicle, but a small mid-sized car. Finally, Szilágyi and Bereczky (2018) stated a VW Golf GTE as a reference vehicle, but the actual material composition is derived from literature and experts' estimates, and Xiong et al. (2019) built their model based on literature values and the GaBi database. Bouter et al. (2020) and Kannangara et al. (2021) used Toyota Prius as the reference vehicle for modeling. In contrast, Öivind Andersson and Börjesson (2021) used the manufacturer's vehicle specification for the 2020 Kia Niro model, combined with typical data from the literature for the LCA model.

Traditional assessments of PHEV usage often assume a fixed daily mileage, which fails to accurately capture the variability inherent in daily driving patterns. Relying on a constant mean value for daily mileage can lead to scenarios where the vehicle predominantly operates in electric mode, leading to minimal fuel consumption, or more frequently in hybrid mode than is reflective of real-world usage. Such discrepancies can significantly impact the outcomes of LCAs and contribute to battery aging, potentially resulting in an inaccurate representation of State of Charge (SOC) profiles. Recent studies Dauphin et al. (2023); Patil et al. (2023); Dai et al. (2025); Kosmidis (2025), emphasize the necessity to consider variable daily mileage linked to recharge scenario in the fuel and energy consumption assessment especially for PHEVs Dauphin et al. (2023).

Zhang et al. (2024) conducted an LCA of PHEVs that accounted for different vehicle operating conditions and battery degradation scenarios. For vehicle operating conditions, they employed three driving cycles: the Federal Test Procedure (FTP) representing urban driving, the Highway Fuel Economy Test (HWFET) simulating highway conditions, and the more demanding US06 cycle, which reflects aggressive driving with high acceleration and engine load. However, their assessment overlooks two critical factors: First, traditional vehicle usage models often assume a fixed daily mileage, which fails to accurately capture the variability in actual driving patterns. Second, the study does not account for the degradation of battery capacity due to temperature, modeling battery degradation solely as a function of energy consumption.

The charging routine plays a crucial role in minimizing fuel consumption by maximizing reliance on the electric mode Philip and Whitehead (2025); Zhu et al. (2024). Regular charging can reduce environmental impacts (depending on a country's energy mix) by minimizing greenhouse gas emissions from fuel combustion and enhancing vehicle performance by ensuring the vehicle operates more in electric mode. Conversely, irregular charging can result in higher fuel consumption, increased operational costs, greater environmental impacts, increased battery aging effect, and reduced vehicle performance.

Despite the detailed modeling approaches, the reviewed literature indicates inconsistencies in fuel consumption values derived from simulation models versus those obtained from literature or empirical data. Moreover, variations in consumption estimates point to the need for more standardized methodologies across studies to improve the comparability of results. These gaps, along with the limited use of battery aging models and reliance on literature-based values, suggest that further research is needed to refine LCA approaches and better understand the long-term sustainability of electrified vehicles.

To tackle these challenges, our study provides a detailed comparison of the environmental impacts of different vehicle types, including battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs), and conventional vehicles (CVs). The main highlights of our study are:

- The development of model-based use-case scenarios incorporating variable daily distance and distributions.
- Integration of battery capacity degradation over time into the LCA calculation.
- Evaluating a full range of environmental impacts using the ReCiPe method, with a structured grouping (clustering) of the impact categories to enhance clarity and interpretation.

The outline of this article is as follows, section 2 presents the methodology adopted and the models developed and used, section 3 presents the results and discussions, followed by conclusions in section 4.

2. Methodology

Figure 1 presents the methodological framework developed for this study. The plug-in hybrid electric vehicle (PHEV), being the most technically complex configuration, is used as the reference platform. The framework is then adapted to other vehicle types—namely battery electric vehicles (BEVs), hybrid electric vehicles (HEVs), and conventional vehicles (CVs)—to enable a consistent and comparative assessment of their environmental impacts.

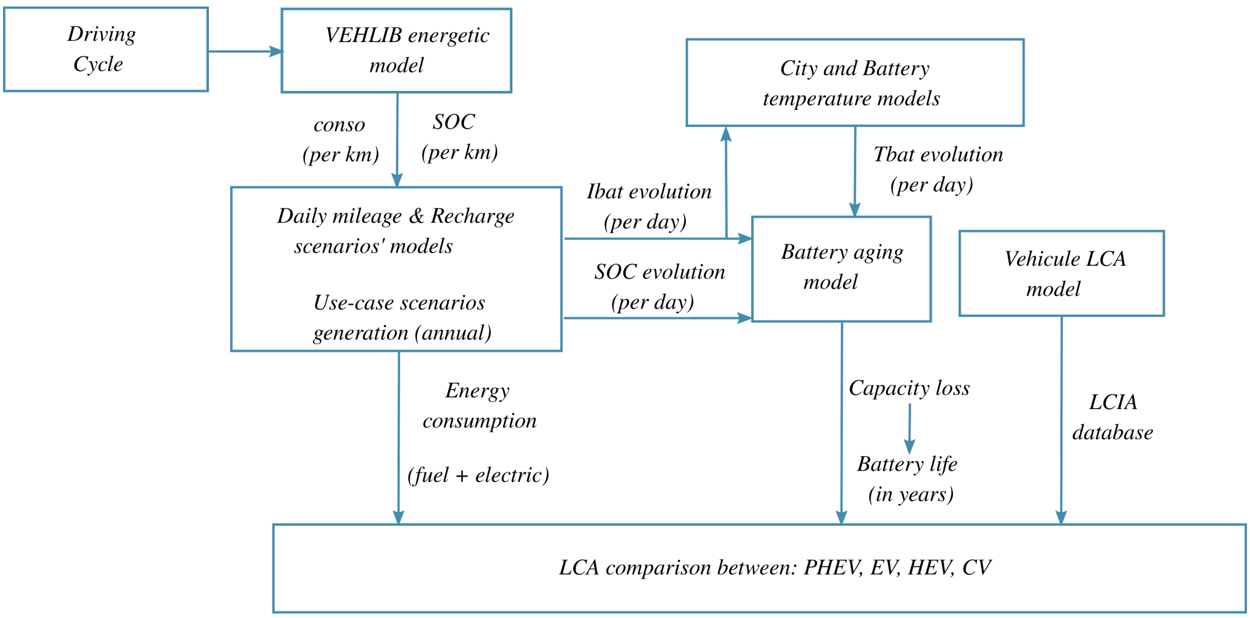


Figure 1: Methodology flowchart to assess LCA for PHEV, EV, BEV, and CV.

The VEHLIB energy model Jeanneret et al. (2010) is used to assess fuel consumption and the evolution of the battery's state of charge (SOC) on a per-kilometer basis, depending on the daily mileage scenario. These outputs serve as essential inputs for building monthly use-case scenarios. When combined with external annual temperature data, the model offers detailed information about the energy consumption patterns, the variation of battery current (I_{bat}), and the daily charging and discharging behavior of the SOC over the course of a year.

The use-case scenario model detailed in Patil et al. (2023); Patil (2024) generates key outputs such as daily driving distances over one year, charging patterns, city-specific and battery temperatures, and inputs for the battery aging model. That study also applied a sensitivity analysis using the conditioned variance method to identify the most influential parameters affecting battery aging and overall environmental impacts.

To develop realistic use-case scenarios, this research draws on data from a comprehensive German mobility survey Follmer (2023), which offers a comprehensive understanding of travel habits, and serves as the primary data source for the study. Given the importance of daily driving distances, particularly for PHEVs Dauphin et al. (2023), the study adopts a statistical approach to accurately capture daily driving and charging patterns. Specifically, it uses a log-normal distribution (see Equation 1) to generate representative daily mileage profiles. Figure 2 presents the frequency distribution versus the daily mileage using parameters $\sigma = 1.06$ and $\mu = 3.11$, as derived from the mobility survey data Redelbach (2016). The figure shows that short trips, typically between 5 and 10 km, are the most common, while longer trips (exceeding 50 km) occur only once or twice per month.

$$Dm = \frac{100}{\sqrt{2\pi}\sigma D} * \exp \frac{(-log(D) - \mu)^2}{2\sigma} \tag{1}$$

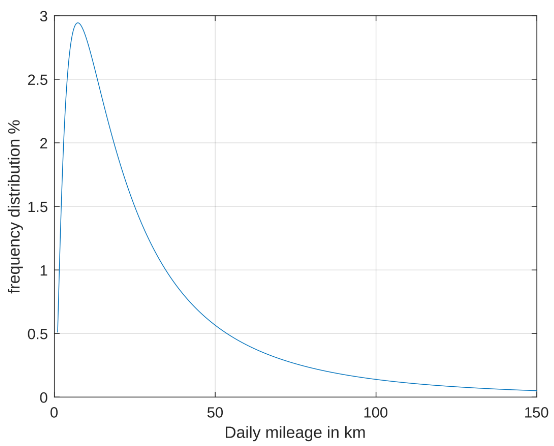


Figure 2: Daily mileage probability from Redelbach (2016); Follmer (2023)

This method ensures that the model mirrors realistic use behaviors, which is crucial for assessing environmental impacts. The battery aging model integrates several key factors, including the evolution of battery current (I_{bat}), state of charge (SOC) variations, and temperature changes throughout the year in various cities, using temperature data from Meteociel (2022), see next section. To calculate capacity loss after one year, the model combines calendar and cycling aging mechanisms based on Eyring laws, validated by previous research Houbbadi et al. (2021); Redondo-Iglesias et al. (2017, 2019). This calculated capacity loss then informs estimates of battery lifespan, factoring in predefined capacity loss limits.

The environmental impacts are evaluated using a Life Cycle Assessment (LCA) approach, implemented through the Brightway framework developed by Mutel (2017), and supported by the Ecoinvent 3.7.1 cut-off database. The model captures all key life cycle stages—manufacturing, operation (including the effects of battery degradation), and end-of-life. Life Cycle Impact Assessment (LCIA) results are calculated across eighteen midpoint indicators following the ReCiPe methodology. These indicators represent specific environmental issues such as climate change, particulate matter formation, or freshwater ecotoxicity, and provide a detailed picture of the environmental burden. These results are compiled into a structured database, with outputs expressed per unit of material (e.g., kilograms of components), energy (e.g., watt-hours), or fuel (e.g., liters). This format enables easy adjustments to component weights or integration of energy consumption values derived from the VEHLIB model. The complete dataset including impact category values for each component and energy source per unit is imported into MATLAB (block located at the bottom of fig. 1). It is then linked with the battery aging model and VEHLIB simulation outputs (energy consumption) to enable a comprehensive and integrated environmental assessment.

In the final stage, environmental impacts of PHEVs, EVs, HEVs and CVs are compared for both French and German electricity mixes. To ensure a consistent and fair basis for comparison, all vehicle types are modeled using the same glider (that is, the body and chassis structure) originally derived from the PHEV platform. This choice is justified by the PHEV's structural complexity and design flexibility, which accommodates both electric and combustion components. The specific powertrain elements for each vehicle type (EV, HEV, CV) are adapted using data from comparable models within the same vehicle segment, sourced from ADAC (2022); A2MAC1 (2023); Hasselwander et al. (2023). A more detailed exploration of battery aging and its implications for vehicle lifetime and life cycle environmental impacts is presented in Section 3.3.

2.1. Battery aging model

In this study, we employed a comprehensive multi-mechanism aging model based on Eyring laws, which has been previously utilized and validated by Redondo-Iglesias et al. (2017, 2019); Houbbadi et al. (2021). The model divides the capacity loss rate, represented as dQ_L/dt, into contributions from calendar aging, cycling at cold temperatures, and cycling at hot temperatures. The formula used for this purpose is as follows:

$$\frac{dQ_L}{dt} = \frac{dQ_{L,cal}}{dt} + \frac{dQ_{L,cyc,cold}}{dt} + \frac{dQ_{L,cyc,hot}}{dt} \tag{2}$$

with:

$$\frac{dQ_{L,cal}}{dt} = A_{cal}.e^{\left(\frac{-E_{a,cal}}{kT}+B_{cal}.SOC\right)}.f(Q_L) \tag{3}$$

$$\frac{dQ_{L,cyc,cold}}{dt} = A_c.|I|.e^{\left(\frac{-E_{a,c}+C_c.|I|}{k(T_o-T)}+B_c.SOC\right)}.f(Q_L) \tag{4}$$

$$\frac{dQ_{L,cyc,hot}}{dt} = A_h.|I|.e^{\left(\frac{-E_{a,h}+C_h.|I|}{kT}+B_h.SOC\right)}.f(Q_L) \tag{5}$$

$$f(Q_L) = \left(\frac{1}{1+b.Q_L^c}\right) \tag{6}$$

In each Eyring law, denoted from equations 3 to 5, the following parameters are used:

- A_i: Pre-exponential term, measured in per unit per day ($p.u.day^{-1}$),
- $E_{a,i}$: Activation energy, expressed in electron volts (eV),
- B_i: State of charge (SOC) influencing parameter, denoted in $p.u^{-1}$,
- C_i: Current influencing parameter, indicated in $hour.p.u^{-1}$, with indices $i = cal, h, c$ representing calendar, hot cycling, and cold cycling, respectively,
- k: Boltzmann constant, measured in electron volts per Kelvin ($eV.K^{-1}$),
- T: Battery temperature, recorded in Kelvin (K),
- T_o: Reference temperature, specified in Kelvin (K),
- I: Current, stated in amperes (A),
- Q_L: Capacity loss at time t, expressed in per unit (p.u.).

Equation 6 signifies the dependency of Q_L in $\frac{dQ_L}{dt}$. This equation implies a decline in the capacity loss rate as the battery undergoes aging, a phenomenon observed in previous research studies Broussely et al. (2001); Spotnitz (2003).

The values of all the parameters identified in equations 3 to 6 were meticulously calibrated against experimental results and data encompassing various states of charge (SOC) and temperatures by Houbbadi et al. (2021); Redondo-Iglesias et al. (2017). This calibration process was undertaken to ensure the model's fidelity in reproducing the observed effects of calendar aging Redondo-Iglesias et al. (2017) and cycling aging tests Song et al. (2014). The used model originates from prior research conducted in our laboratory and has been refined using extensive experimental data across various SOC levels and temperatures. Hence, we maintain confidence in the model's accuracy.

2.2. LCA model setup

The LCA methodology applied in this study follows the ISO 14040/44:2006 standards. The goal of this LCA analysis is to compare the environmental impacts of different vehicle types, including electric vehicles (EVs), plug-in hybrid electric vehicles (PHEVs), hybrid electric vehicles (HEVs), and conventional vehicles (CVs), by factoring in battery aging under realistic usage scenarios, derived from assessments of daily mileage.

The initial reference flow for this study is “one kilometer driven by the investigated vehicle, also known as vehicle kilometers”. The primary functional unit is “200,000 kilometers driven in a typical European medium-size (C-segment) passenger PHEV under Artemis driving conditions (a procedure based on extensive analysis of real-world European driving data and include three driving schedules: urban, rural road, and motorway André (2004)), satisfying minimum dynamic performances requirements”.

To assess environmental impacts across multiple categories, the study uses the ReCiPe midpoint methodology Huijbregts et al. (2017), a widely recognized approach for life cycle impact assessment.

The primary data for this LCA model, including vehicle component group masses and material compositions are sourced from an internal Deutsches Zentrum für Luft- und Raumfahrt (DLR) database DLR (2019). The complete life cycle inventory (LCI) datasets are available from the authors upon request.

2.2.1. Manufacturing phase

Figure 3 presents the background and foreground system of the LCA model. The modeling of the background system, material compositions, electricity, and distinct manufacturing processes for the electric machine, power inverter, lithium-ion battery (LIB), and internal combustion engine (ICE) components relies on the LCA database, specifically Ecoinvent version 3.7.1. The foreground system including the manufacturing processes and major subcomponent details, such as the ICE drivetrain, electric machine, power inverter, and Li-ion battery system, are sourced from the literature on previous LCAs with data quality close to primary data.

During the manufacturing phase, component production is assumed to take place in Germany, with transport distances estimated accordingly. Scalable models for the power inverter and electric machine are based on Nordelöf (2019); Nordelöf and Tillman (2018), while the neodymium magnet is sourced from China, as noted by Marx et al. (2018). The Li-ion battery system is modeled after Dai et al. (2018), with battery modules supplied by Samsung SDI. The internal combustion engine (ICE) powertrain components and manufacturing process data come from various sources, including Hawkins et al. (2013); Hoag and Dondlinger (2016). The rest of the vehicle (RoV), including the glider, fluids, mounts, and final assembly, is assigned to the RoV category due to its significant mass. The glider is modeled using Ecoinvent data for ”glider production, passenger car [GLO]” and assembly data from Hawkins et al. (2013).

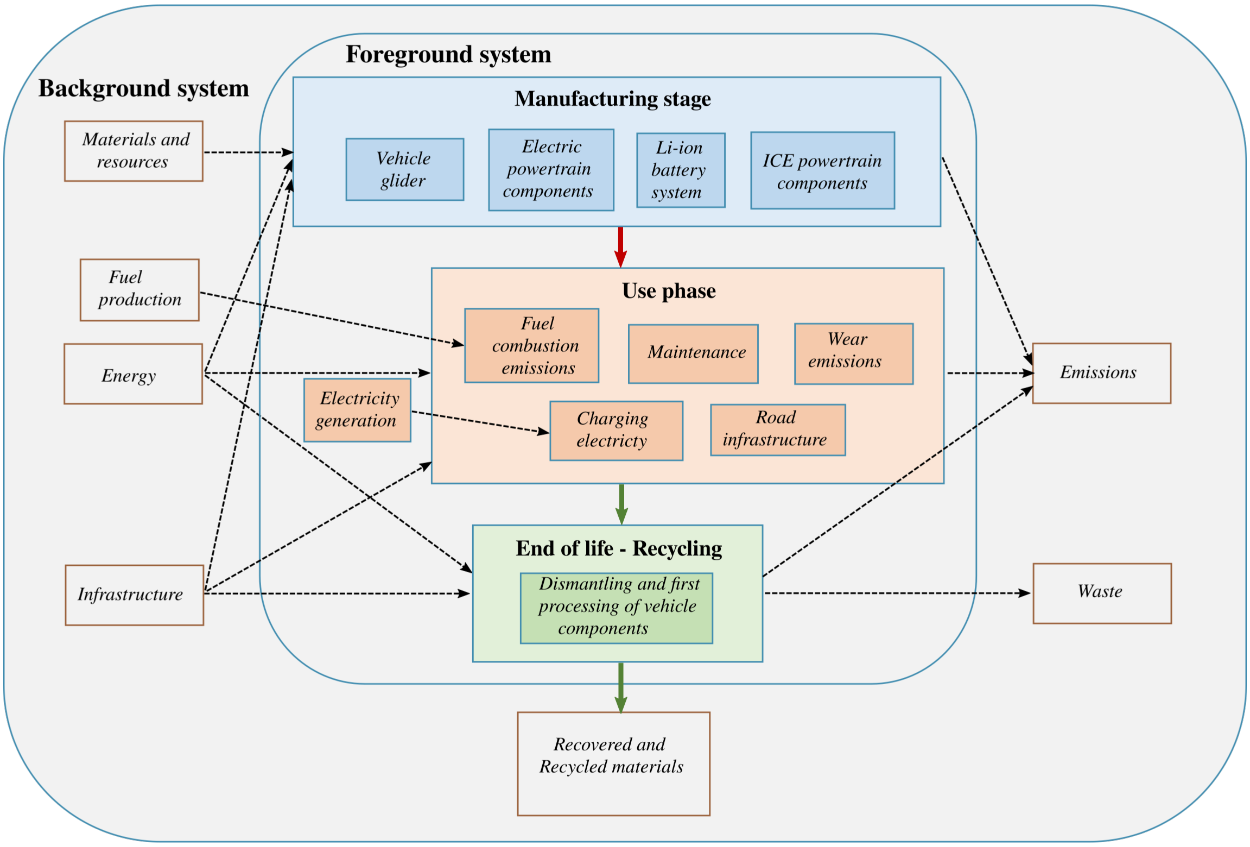


Figure 3: Background and foreground system of the LCA model

2.2.2. Use phase

The use phase is segmented into five key sub-processes: maintenance, fuel combustion emissions, wear emissions, road infrastructure, and provision of charging electricity.

- **Maintenance:** This contains activities such as fluid exchanges, tire replacements (the lifetime of a tire is assumed to be 50,000km), and SLI (Start-Light-Ignition) battery swaps after 6 years. Assumptions regarding these maintenance tasks are derived from insights provided by a PHEV expert at the Institute of Vehicle Concepts, DLR, Fröhlich (2019) and listed in Table 1.

Table 1: Maintenance frequency for 200,000km Fröhlich (2019).

Annual mileage (km)	Vehicle use (years)	Engine oil (n)	Gearbox oil (n)	Braking fluid (n)	Washing fluid (n)	Tires (n)	SLI battery (n)
13739	14.3	11	1	5	7	3	1

- **Fuel combustion emissions:** This category comprises emissions like CO_2, CO, NOx, etc., originating from the combustion of fuel (petrol with 5% Vol. ethanol that is representative of the fuel used in test drives Ehrenberger et al. (2019)). This also includes the production of petrol using the ecoinvent dataset *petrol production, 5% ethanol by volume from biomass*. Validation of these emissions is achieved through test drives conducted by DLR (German Aerospace Center) Ehrenberger et al. (2019).

- **Wear emissions:** This includes emissions from road wear, tire wear, and brake wear, sourced from ecoinvent datasets *treatment of road wear emissions, passenger car [RER], treatment of tire wear emissions, passenger car [RER] and treatment of brake wear emissions, passenger car [RER]*, where RER refers to the European region.
- **Road infrastructure:** For quantifying road infrastructure utilization, the ecoinvent dataset *road construction [Switzerland (CH)]* is used.
- **Provision of charging electricity:** The background data for electricity generation were modeled using the Ecoinvent database, while the repartition of energy sources within the 2022 electricity generation mix was derived from the total net electricity generation data provided by Fraunhofer (2022). The charging electricity therefore reflects the national electricity mix for the year 2022. The charging losses, measured internally between the wall outlet and the battery for the VW Golf VIII GTE, are estimated at 15%.

The calculation of the fuel and electrical consumption during the vehicle's lifetime is carried out on a simulation software VEHLIB Jeanneret et al. (2010), on the urban, extra-urban, and motorway part of the Artemis driving cycle, using a battery aging model to calculate the capacity lost by the battery during the vehicle's life and hence the number of times the battery needs to be replaced.

2.2.3. End-of-life

The LCA model uses the "cut-off approach," consistent with OEM LCA studies, Sjöqvist and Ibrahem (2021). In this method, emissions from the end-of-life (EOL) phase are limited to the dismantling and initial processing of vehicle components. Materials in the Li-ion battery (LIB) are recovered through hydro-metallurgical processing, while further recycling is allocated to future users and not included in this LCA.

2.3. LCA calculation

The initial step in this calculation involves importing the life cycle impact assessment (LCIA) results database generated from the life cycle assessment (LCA) model. As detailed, this database contains results for eighteen ReCiPe midpoint impact categories corresponding to processes. For instance, it includes information such as the impact results of manufacturing 1 kilogram of a LIB across eighteen environmental indicators, including climate change, human toxicity, and air quality, among others, because of the linearity of all the modeled processes (the effect of emissions increases linearly with increasing quantity of each process).

The total LCA calculation (7) is divided into three primary phases: the manufacturing phase, the use phase, and the end-of-life (EOL) phase.

$$Total = Manufacturing + Use\,phase + EOL \tag{7}$$

The manufacturing phase includes the production of components such as the lithium-ion battery (LIB) system, electric machine, power inverter, electric powertrain system, internal combustion engine (ICE), transmission system, ICE electronics, and ICE powertrain system. The presence and contribution of these components vary depending on the vehicle type. For instance, in the case of a conventional vehicle, all electric powertrain components and the LIB are not present, and their associated impacts are therefore considered null. Conversely, the remainder of the vehicle commonly referred to as the glider, is assumed to be identical across all vehicle types.

The use phase includes emissions associated with fuel and electricity consumption. This includes both upstream emissions from fuel production and downstream emissions from fuel combustion, as well as the environmental impacts of electricity used for vehicle charging. These contributions are vehicle-dependent; for example, in the case of a BEV, the impacts related to ICE components and fuel combustion are excluded. Road infrastructure and vehicle maintenance are considered uniform across all scenarios and are therefore treated as independent of vehicle type.

The end-of-life phase incorporates the disposal and processing of used powertrain components such as the LIB, electric machine, and ICE according to the specific vehicle configuration. The treatment of the glider and manual dismantling operations is assumed to be consistent across all vehicle types.

It is important to note that the glider and non-powertrain components are assumed to be identical across all vehicle types, ensuring that differences in impacts are solely attributable to the powertrain, fuel, and electricity-related aspects.

3. Results

In this section, we compare various types of vehicles: Plug-in Hybrid Electric Vehicle (PHEV), Electric Vehicles (EVs), Hybrid Electric Vehicle (HEV), and Conventional Vehicles (CVs). For the PHEV, we consider a scenario based on the standard VW Golf GTE representative of a midsize vehicle. It is important to note that the vehicle chassis and body, known as the glider, is the same VW Golf GTE for all vehicle types. However, the component sizes for the EVs, HEV, and CVs are specifically based on the vehicles in the same class.

The component specifications for each vehicle, along with the use-case parameters applied in the analysis, are detailed in Tables 2 and 3, respectively. The characteristics listed in the table are parameters in our model and can be changed to any desired values, making this work flexible as per the requirements of the user of this approach. For instance, future decarbonized electricity mixes, or different battery sizes can be easily considered. While this study focuses on four representative vehicle types for the sake of clarity, the model is flexible and can easily be extended to other configurations. By modifying component sizes especially those of the battery, electric machine (EM), and internal combustion engine (ICE), a wide range of vehicles can be analyzed. A previous parametric study Patil (2024) confirmed that although changes in EM and ICE size do influence life cycle results, their impact is generally less significant than that of battery capacity, which remains the dominant factor. Further sensitivity analyses carried out in earlier studies Patil et al. (2023); Patil (2024) explored a broad set of parameters, including vehicle use, component sizes, temperature, modeling approaches, and battery aging. These studies highlighted that the most influential factors vary depending on the specific impact category but consistently showed that electricity mix, battery size, total lifetime distance, annual mileage and temperature (mainly for extreme conditions) are among the most sensitive parameters.

In the present work, to keep the scope manageable while still capturing key variations, we focus on two contrasting electricity mixes, France and Germany, and provide selected results related to battery size, particularly for BEV and PHEV, where larger battery capacities are typically involved.

The components of the vehicles are provided in Table 2. The four vehicle configurations analyzed are as follows:

- A PHEV based on the standard Volkswagen Golf GTE.
- A BEV equipped with a 50 kWh battery and a 110 kW EM,
- A HEV with a small 1.4 kWh battery, a 53 kW EM, and a downsized 72 kW ICE, reflecting classical values found in vehicles such as the Toyota Prius.
- A CV powered by the same 110 kW ICE as used in the PHEV Golf.

In this section, two types of scenarios are presented, differentiated by the electricity mixes of France and Germany. The environmental data for each scenario are based on climatic conditions in Lyon (France) and Berlin (Germany), respectively from Meteociel (2022), which represent two typical towns in France and Germany. The vehicle usage parameters correspond to average driving conditions, as detailed in Table 3. It is assumed that vehicles are charged daily, with an average annual mileage of 13,739 km consistent with reported values for Germany Follmer (2023), and similarly observed in France. In this part of the analysis, no battery replacement is considered, as it is generally unrealistic to expect a battery pack to be replaced shortly before the vehicle reaches 200,000 km. A more detailed analysis of battery aging, including its effect on vehicle lifetime and life cycle impacts, is presented in Section 3.3.

By combining the four vehicle types with the two regional scenarios, six distinct cases are analyzed. CV and HEV are assumed to exhibit the same environmental impacts in both France and Germany, given their limited dependence on electricity.

The study applies the ReCiPe midpoint (H) methodology in combination with the Ecoinvent 3.7.1 cut-off system model. ReCiPe evaluates eighteen environmental impact categories, which makes it difficult to present and interpret all results at once in a concise way. Therefore, the analysis is structured in two parts. First, a focused comparison is provided for global warming potential (GWP), broken down by each major life cycle phase (see Section 3.1 and Section 2.3). In a second step, the full set of ReCiPe midpoint indicators is presented and analyzed for the six representative vehicle cases (see Section 3.2).

Table 2: Components sizes of the vehicles compared: PHEV, EV, HEV, and CV.

Definition	PHEV	BEV	HEV	CV
battery energy in kWh	13 kWh	50 kWh	1.4 kWh	
maximum power of the electric machine in kW	90 kW	110 kW	53 kW	
maximum power of the engine in kW	110 kW		72 kW	110 kW

Table 3: Uses characteristics of the vehicles compared: PHEV, EV, HEV, and CV

Uses characteristics	
number of km per year	13739 km
charging mode	after each day
city of dwelling	lyon/berlin
battery capacity loss limit	20 %
total distance travel during vehicle lifetime	200000 km
charging electricity-mix	French/German
charging efficiency	85 %
driving cycle	WLTC

3.1. Global Warming potential

Figure 4 presents the GWP, measured in grams of CO_2-equivalent per kilometer, for various vehicle types BEV, HEV, PHEV, and CV in both Germany and France. Since the electricity mix varies significantly between the two countries, BEVs and PHEVs operating in France and Germany are presented separately (BEVfra, BEVger, PHEVfra, PHEVger).

The GWP is broken down into three main life cycle stages: manufacturing, use phase, and end-of-life. The manufacturing stage is further divided into two parts: battery production and the manufacturing of the rest of the vehicle. The use phase is detailed across four categories:

- electricity production, which accounts for emissions from producing electricity used by the vehicle.
- fuel combustion, referring to emissions released directly from the vehicle's exhaust during operation.
- fuel production, which includes the environmental impact of extracting, refining, and transporting fuel to distribution stations.
- and other operational impacts, such as those associated with road infrastructure and maintenance.

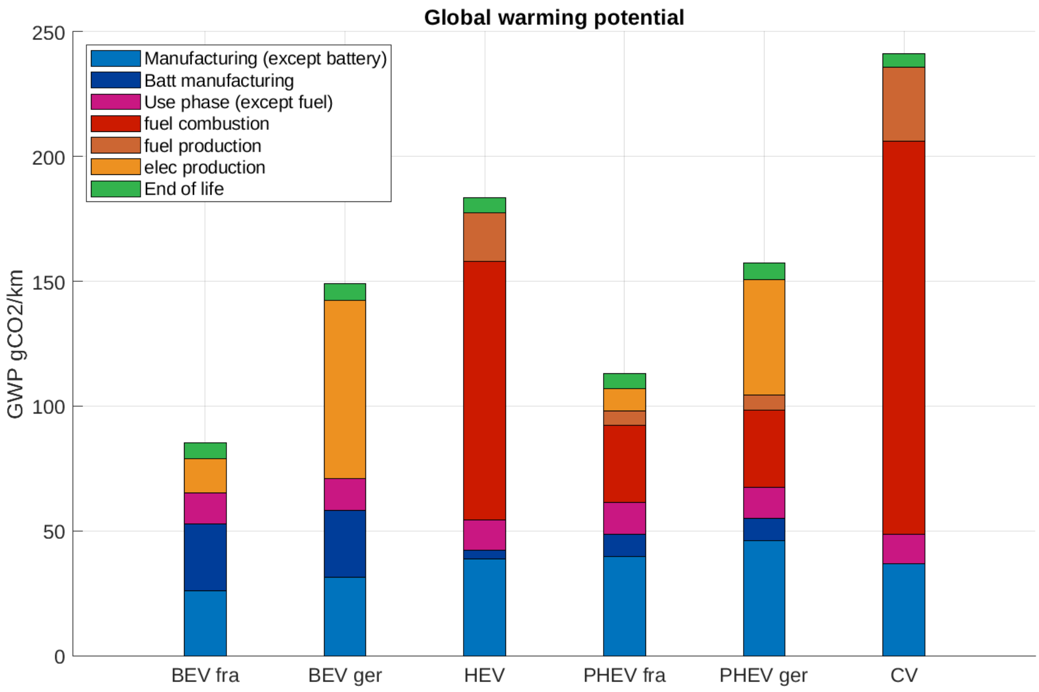


Figure 4: Phase-wise GWP impact comparison between various types of vehicles for France and Germany in g CO_2-Eq/km.

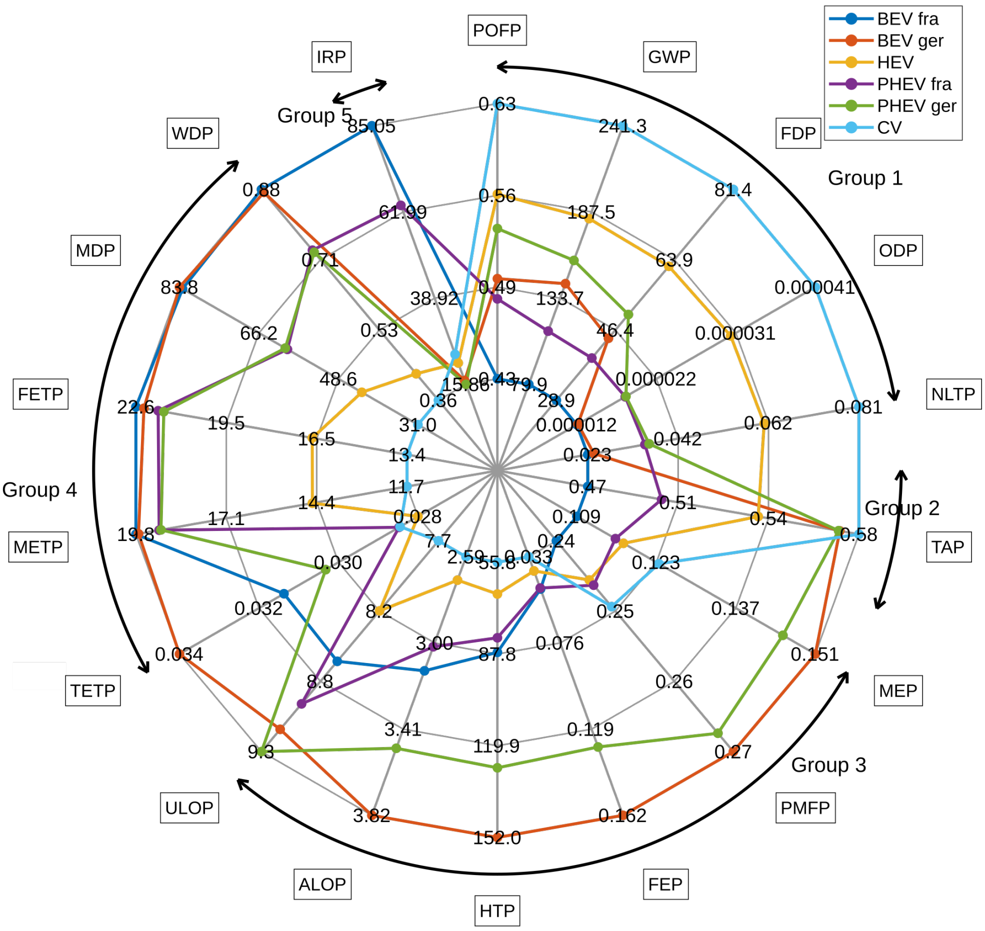
The differences in use-phase and total GWP emissions for EVs and PHEVs between Germany and France are driven primarily by the contrast in their electricity mixes. Due to Germany's increased dependence on fossil fuels in electricity generation, EVs and PHEVs operated there produce significantly more emissions during the use phase compared to those in France. As a result, their overall GWP emissions are also significantly higher in Germany.

Fuel consumption is a critical factor for conventional Golf vehicles (CVs). Producing and burning each liter of petrol generates approximately 2.9 kg of CO_2-equivalent emissions, 2.44 kg from combustion and 0.46 kg from fuel production and transportation (based on EcoInvent values for low-sulfur petrol). As a result, the 110 kW CV emits about 187.1 g CO_2-Eq per kilometer from fuel use alone. The hybrid electric vehicle (HEV) produces roughly 189.4 g CO_2-Eq/km from fuel consumption. For plug-in hybrid electric vehicles (PHEVs), emissions arise from both fuel and electricity consumption. In France, the PHEV emits approximately 8.7 g CO_2-Eq/km from electricity and 37.5 g CO_2-Eq/km from fuel, totaling around 46.05 g CO_2-Eq/km—of which 31.4 g CO_2-Eq/km is attributed to fuel combustion. In Germany, where the electricity grid has a higher carbon intensity, emissions from electricity use increase to 46.2 g CO_2-Eq/km, bringing the PHEV's total use-phase emissions to approximately 104.1 g CO_2-Eq/km. For fully electric vehicles (BEVs), emissions depend entirely on electricity consumption. With an energy consumption of 132 Wh/km, the BEV produces 13 g CO_2-Eq/km in France and 69.3 g CO_2-Eq/km in Germany, reflecting differences in grid carbon intensity. Additional emissions stem from road infrastructure construction, as well as maintenance activities such as fluid replacements and tire wear. Overall, in Germany, the BEV exhibits the lowest total global warming potential (GWP) impact at 136.5 g CO_2-Eq/km, followed closely by the PHEV at 157.6 g CO_2-Eq/km. In France, BEVs achieve the lowest GWP impact of 74.5 g CO_2-Eq/km, approximately half that of PHEVs and one-third that of CVs.

GWP is one of the most widely recognized and policy-relevant indicators for assessing climate impacts. However, it does not capture the full range of environmental burdens associated with vehicle life cycles. Therefore, while GWP is examined in detail as a first step, a comprehensive view of other environmental impacts is provided in the following section through the full set of ReCiPe midpoint impact categories.

3.2. All Impacts Categories

Figure 5 provides a radar chart comparing the environmental performance of different vehicle types across the eighteen ReCiPe midpoint impact categories.



ALOP : agricultural land occupation m^2.year
GWP : global warming g.CO_2.eq
FDP : fossil depletion g.oil.eq
FETP : freshwater ecotoxicity 1.4.g.DCB.eq
FEP : freshwater eutrophication g.P.eq
HTP : human toxicity 1.4.g.DCB.eq
IRP : ionising radiation g.U-235.eq
METP : marine ecotoxicity 1.4.g.DCB.eq
MEP : marine eutrophication g.N.eq
MDP : metal depletion g.Cu.eq
NLTP : natural land transformation m2
ODP : ozone depletion g.CFC 11.eq
PMFP : particulate matter formation g.PM10.eq
POFP : photochemical oxidant formation g.NMVOC.eq
TAP : terrestrial acidification g.SO_2.eq
TETP : terrestrial ecotoxicity 1.4.g.DCB.eq
ULOP : urban land occupation m^2.year
WDP : water depletion m^3

Figure 5: Radar representation for comparison between different vehicle types for ReCiPe impact categories

In this section, we provide a broader overview of the environmental impacts across all ReCiPe midpoint categories. Unlike the detailed breakdown presented for GWP, this comparison focuses only on the total (global) impact values. Figure 5 illustrates the environmental performance of the six representative vehicle cases using the ReCiPe method. The comparison includes the same vehicle as in sec. 3.1. Six vehicles, BEV fra, BEV ger, HEV, PHEV fra, PHEV ger, and CV are compared across all 18 ReCiPe impact categories, listed at the bottom of the figure. The results are displayed in a radar chart, where the vehicle with the lowest impact appears on the inner circle and the one with the highest impact on the outer circle. Consequently, the scale varies for each impact category.

To facilitate a clearer interpretation, the impact categories have been grouped clockwise into six distinct clusters, based on the categories where certain vehicle types exhibit the highest relative contributions:

- Group 1 : POFP (photochemical oxidant formation), GWP (global warning), FDP (fossil depletion), ODP (ozone depletion), NLTP (natural land transformation)
- Group 2 : TAP (terrestrial acidification)
- Group 3 : MEP (marine eutrophication), PMFP (particule matter formation), FEP (freshwater eutrophication), ALOP (agricultural land occupation), HTP (human toxicity), ULOP (urban land occupation)
- Group 4 : TETP (terrestrial ecotoxicity), METP (marine ecotoxicity), FETP (freshwater ecotoxicity), MDP (metal depletion), WDP (water depletion)
- Group 5 : IRP (ionizing radiation)

Figure 5 has been split, and the impacts for groups 1, 3, and 4 are shown in separate figures to make the information easier to read. Group 1 (Fig. 6) is composed of impacts primarily driven by fuel consumption and in second order production. Emissions from electricity explain why electrified vehicle presents sometimes higher impact in france and germany. CV shows the highest values, generally followed by HEV and PHEV. An exception is observed for TAP, where PHEVger exhibits a higher impact than HEV, due to the Germany's electricity mix, which is partly based on coal.

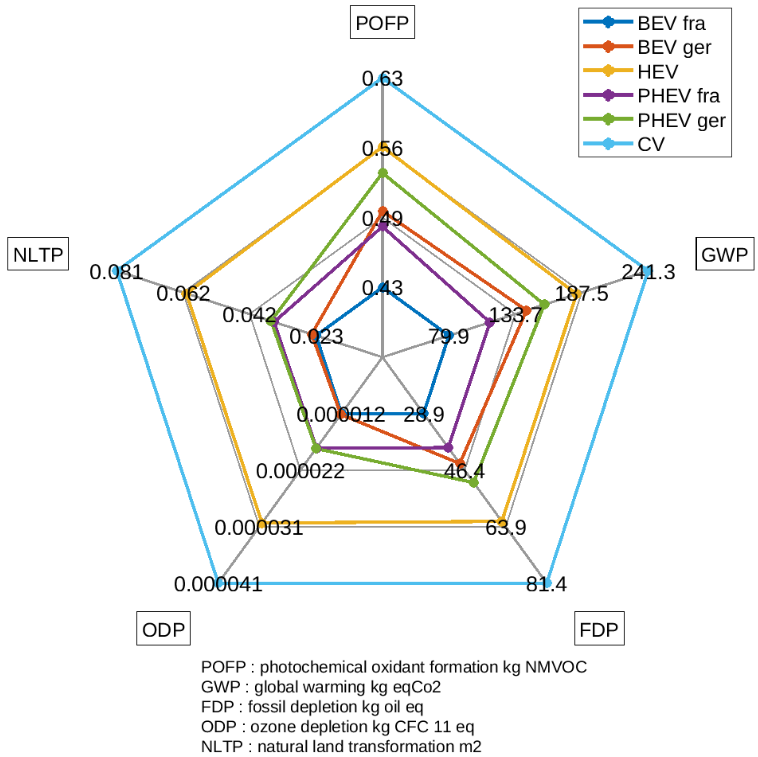


Figure 6: Radar representation for comparison between different vehicle types for POFP, GWP, FDP, ODP, NLTP, impact categories (Group 1)

Group 2 includes only TAP, which is primarily influenced by fuel consumption and electricity production. BEV and PHEV vehicles operating in Germany therefore exhibit higher impacts.

For Group 3 (Fig. 7), the impacts are mainly driven by the electricity mix, with battery production playing a secondary role. BEV and PHEV vehicles in Germany show the highest values, typically followed by their counterparts in France.

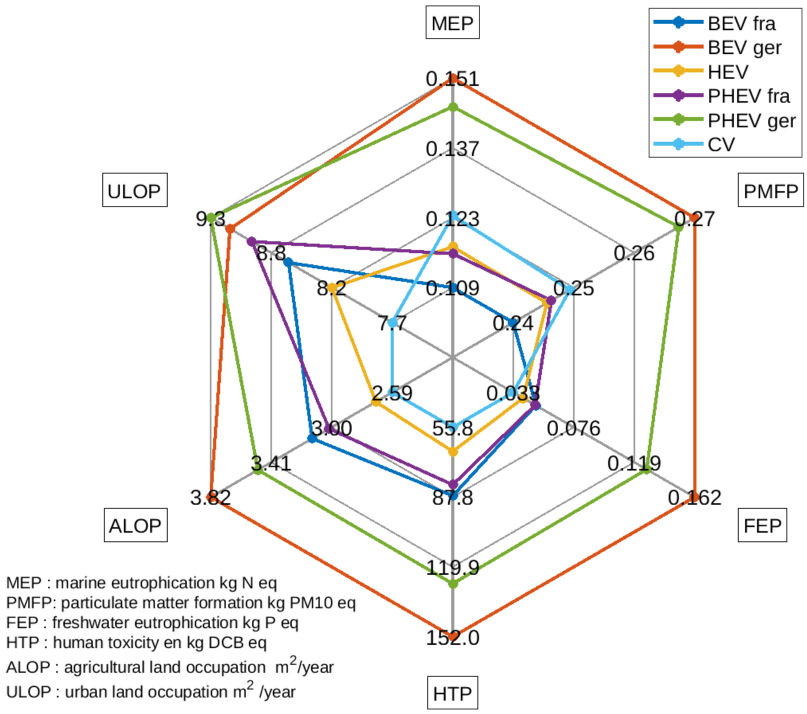


Figure 7: Radar representation for comparison between different vehicle types for MEP, PMFP,FEP,ALOP, HTP,ULOP impact categories (Group 3)

In Group 4 (Fig. 8), the impacts are dominated by vehicle manufacturing. The substantial contribution of battery production leads to higher values for BEV, followed by PHEV, then HEV and finally CV.

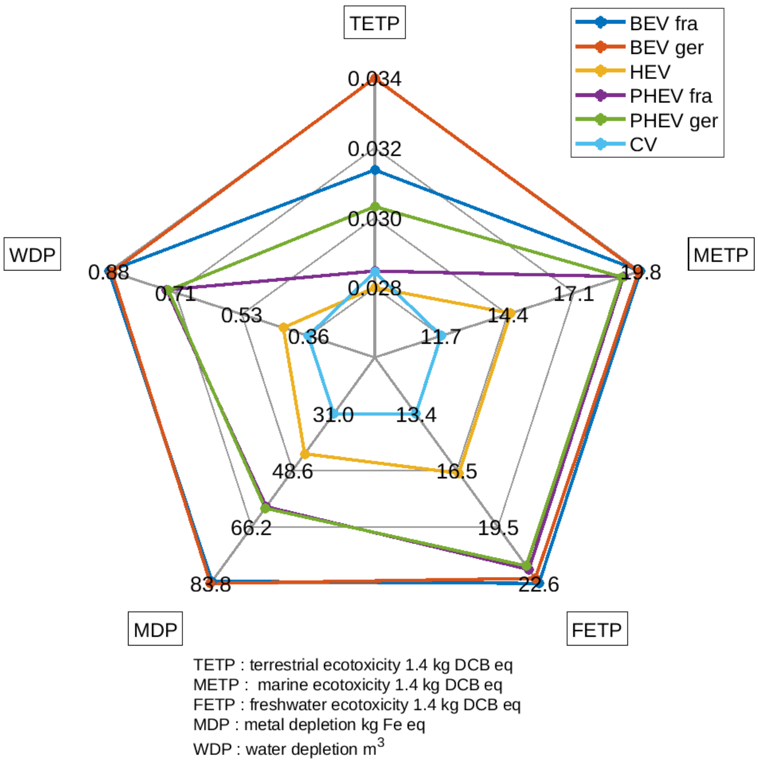


Figure 8: Radar representation for comparison between different vehicle types for TETP, METP, FETP, MDP, WDP, impact categories (Group 4)

Group 5, which includes only IRP, is strongly affected by the high share of nuclear power in France's electricity mix (approximately 75%). Consequently, BEVfra and PHEVfra exhibit the highest impacts in this category.

Across the five clusters, BEVfra generally shows the lowest overall environmental burden, benefiting from France's low-carbon electricity. In contrast, CV consistently ranks highest in fuel-related impact categories, while PHEVger and BEVger often display elevated impacts in electricity-sensitive categories, reflecting Germany's more carbon-intensive power mix. HEV occupies an intermediate position, with moderate impacts across most categories.

It is important to note that battery replacement over the vehicle's lifetime is not considered in the current scenario. Only the gradual capacity loss due to battery aging is included. As a result, the distribution of environmental impacts may vary under different usage conditions or technical assumptions. To explore the effects of battery degradation further, the following section presents additional scenarios focusing on BEV and PHEV configurations with varying battery capacities.

3.3. Influence of Battery Aging on Life Cycle Impacts

In line with the growing trend to increase the driving range of electrified vehicles, additional configurations are introduced to assess the effect of battery size on BEV and PHEV.

BEVs equipped with a 40kWh and a 60 kWh battery and a PHEV with a 20 kWh battery are studied. Since battery replacement is generally not expected during the vehicle's lifetime, this study assumes that the vehicle is retired once its battery capacity falls below a functional threshold. As a result, the total environmental impact per kilometer is directly linked to the cumulative distance the vehicle can travel before this threshold is reached.

Table 4 presents the estimated maximum operational years and distance for each vehicle until a 20% capacity loss occurs. These values are shown for the two climate and electricity mix scenarios corresponding to France and Germany. This analysis focuses on BEV and PHEV configurations, as battery degradation is negligible in HEVs given their limited battery usage range (typically between 40% and 70%) and is not applicable to conventional vehicles.

Table 4: Maximum years and kilometers to reach 20% of capacity loss

City	**Lyon**				**Berlin**			
Vehicle	BEV 40 kWh	BEV 60 kWh	PHEV 13 kWh	PHEV 20 kWh	BEV 40 kWh	BEV 60 kWh	PHEV 13 kWh	PHEV 20 kWh
Years	15.0	16.0	12.4	13.8	16.0	17.4	12.9	14.5
1000 km	210	224	173	192	225	243	180	203

Table 4 shows that PHEVs generally do not reach the 200,000 km reference used in earlier sections, but also confirms that battery replacement at approximately 173,000 km is not a realistic scenario. Increasing battery capacity slightly extends the vehicle's usable lifespan; however, the gain in lifetime is proportionally smaller than the increase in battery size.

Figure 9 presents the GWP per kilometer for the eight vehicles described in Table 4, including the two BEVs and two PHEVs operated in France and Germany. The red lines indicate the GWP emissions from the reference scenarios for PHEVs and BEVs, previously presented in Figure 4, providing a basis for comparison.

The results reveal contrasting trends between BEVs and PHEVs. For BEVs, increasing battery size leads to a higher GWP per kilometer. This is primarily due to the higher manufacturing impact associated with larger batteries, which is not sufficiently offset by an extended vehicle lifetime. In contrast, for PHEVs, a larger battery slightly reduces the GWP per kilometer. This improvement is explained by a greater share of driving performed in electric mode, resulting in lower emissions during the use phase. Even in Germany, where electricity production is more carbon-intensive, the larger-battery PHEV shows a slight GWP advantage driven by an 11% increase in total distance traveled and improved electric driving share. However, when compared to the reference scenario results presented in Figure 4, the differences in GWP emissions remain relatively limited. This is because the maximum driving distances before reaching 20% battery capacity loss, as shown in Table 4, are close to the 200,000 km baseline used in the reference scenario presented in Table 3.

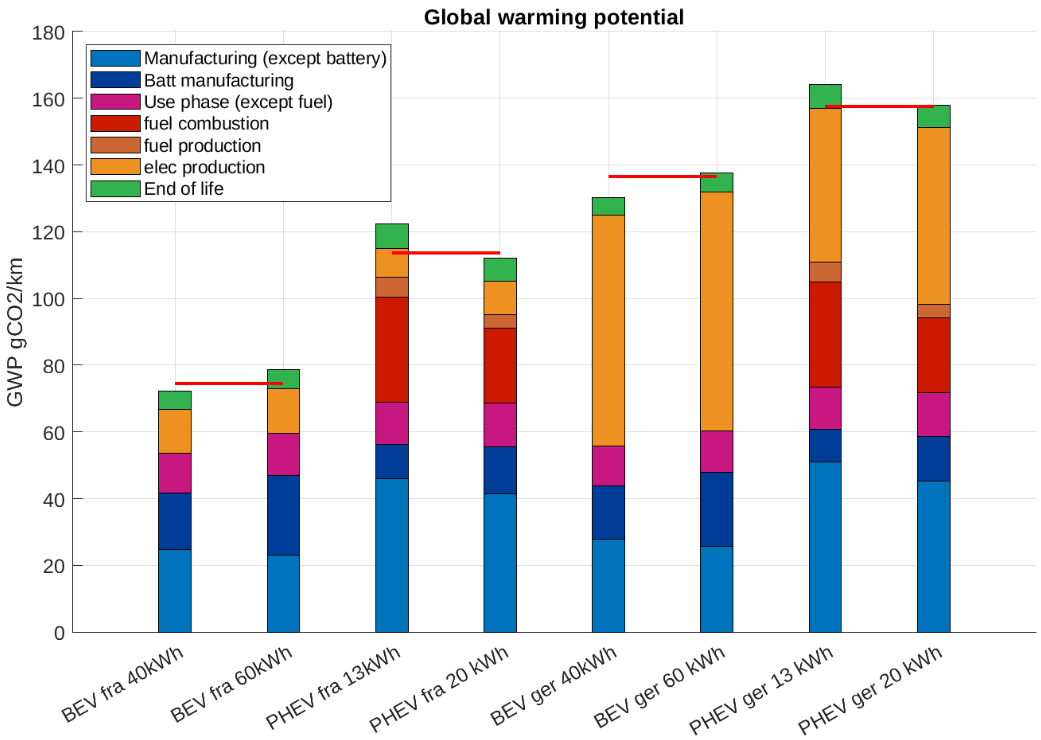


Figure 9: Phase-wise GWP impact comparison between BEV and PHEV for different size of batteries for France and Germany in g CO_2-Eq/km. Red lines show reference GWP values from Figure 4.

Figure 10 presents the complete set of ReCiPe midpoint impacts for BEVs and PHEVs, with vehicles operating in France shown in the upper plot and those in Germany in the lower plot. To facilitate interpretation, the impact categories have been clustered based on similar patterns of relative contributions among the vehicle types. The clustering also highlights the influence of regional context, particularly the differences between the French and German electricity mixes. Three distinct groups of impact categories are proposed:

- Group 1 : TAP, MEP, PMFP, FETP, METP, ALOP, ULOP, POFP, GWP, FDP, ODP, NLTP,
- Group 2 : TETP, WDP, MDP,
- Group 3 : IRP, HTP, FEP.

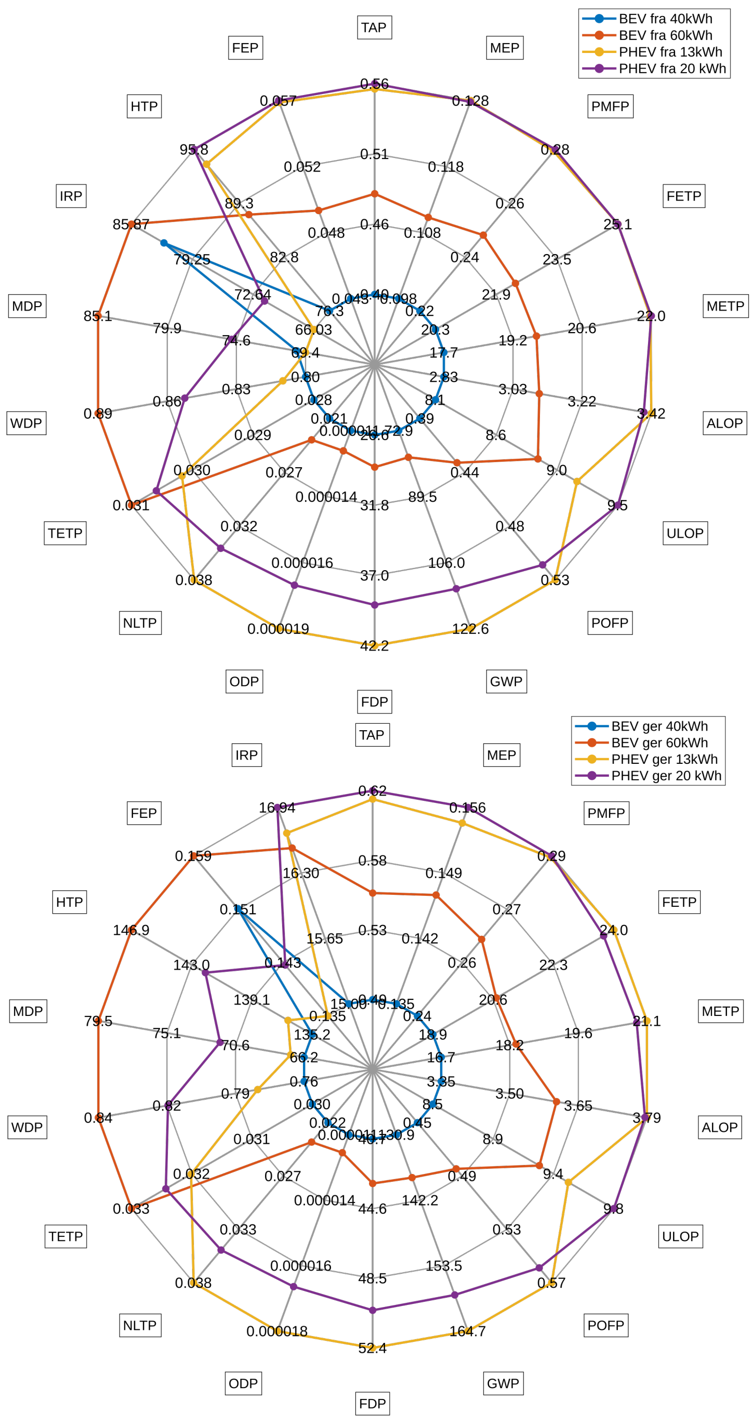
In Group 1, PHEVs exhibit the highest environmental impacts, followed by the BEV with a 60 kWh battery and the BEV with a 40 kWh battery, both in France and Germany. The greater impact of the 60 kWh BEV compared to the 40 kWh version is likely due to the increased burden from battery manufacturing. For impact categories such as TAP, MEP, PMFP, FETP, METP, and ALOP, the PHEVs show relatively similar values, suggesting that these impacts are strongly influenced by the thermal powertrain components.

Interestingly, the PHEV with the 20 kWh battery shows lower values than the 13 kWh version in categories like POFP, GWP, FDP, ODP, and NLTP. This can be attributed to reduced fuel consumption, as a larger share of energy use shifts to electricity. Conversely, for ULOP, the PHEV13kWh performs slightly better, likely because the smaller battery reduces manufacturing-related land occupation impacts.

Group 2 reflects the combined influence of battery manufacturing and electricity production. In this group, the BEV with the 60 kWh battery consistently shows the highest impact in both France and Germany, highlighting the dominant role of battery size in these impact categories.

In Group 3, however, the electricity mix plays a decisive role, leading to markedly different outcomes between the two countries. For instance, in France, the IRP impact is substantially higher for more electrified vehicles due to the dominance of nuclear power in the electricity mix. In Germany, by contrast, the pattern more closely resembles Group 1, with less variation across vehicle types. For FEP, the German electricity mix results in greater impact than in France. With regard to HTP, the values align with Group 1 in France; however, in Germany, the continued presence of coal in the energy mix drives significantly higher impacts across all vehicle types, with a slight peak for the BEV60kWh.

In conclusion, the results presented in this section should be interpreted with caution, as they are highly sensitive to several parameters, particularly the threshold for battery capacity loss at which a vehicle is assumed to be retired from use. Within the scope of this case study, BEVs generally demonstrate lower impacts than other vehicle types across most ReCiPe categories in both France and Germany. Moreover, for all impact categories, a smaller battery consistently results in lower environmental burdens, raising critical questions about the sustainability of increasing battery sizes in BEVs. For PHEVs, the shift from fuel-based to electricity-based propulsion enables some environmental benefits; in these cases, increasing battery size can reduce certain impacts, particularly those related to fuel combustion.



ALOP : agricultural land occupation m^2.year
GWP : global warming g.CO_2.eq
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IRP : ionising radiation g.U-235.eq
METP : marine ecotoxicity 1.4.g.DCB.eq
MEP : marine eutrophication g.N.eq
MDP : metal depletion g.Cu.eq
NLTP : natural land transformation m2
ODP : ozone depletion g.CFC 11.eq
PMFP : particulate matter formation g.PM10.eq
POFP : photochemical oxidant formation g.NMVOC.eq
TAP : terrestrial acidification g.SO_2.eq
TETP : terrestrial ecotoxicity 1.4.g.DCB.eq
ULOP : urban land occupation m^2.year
WDP : water depletion m^3

Figure 10: Radar representation for comparison between different vehicle types for different size of batteries for France and Germany in g CO_2-Eq/km.

4. Conclusions

As the world moves toward a more sustainable future, electrifying transportation is a key strategy in the fight against climate change. While global and EU policies are pushing for this transition, the broader environmental impacts of electric vehicles (EVs), particularly those related to battery production, are still under-explored. LCA plays a crucial role in evaluating the full environmental footprint of these vehicles, ensuring that the shift aligns with sustainability goals, from production to disposal.

This study employed previously developed, realistic driving scenarios to model diverse daily and annual usage and recharge patterns. It further investigated the effects of battery aging on vehicle performance and environmental impacts by integrating dynamic battery degradation models within the LCA framework. This approach provides a more accurate depiction of how battery degradation influences the environmental impacts of PHEVs and BEVs over time.

Environmental impacts comparison between the different vehicle types shows how regional electricity mixes, manufacturing, and battery size together shape the environmental impacts of different vehicle types. In France's cleaner energy context, battery electric vehicles (BEVs) and plug-in hybrids (PHEVs) have much lower greenhouse gas emissions than in Germany, where electricity is still carbon-heavy. BEVs consistently perform best, especially with low-carbon power, while PHEVs do better in France but have higher emissions in Germany. Conventional vehicles emit the most, mainly from fuel, and hybrids fall somewhere in between.

Our analysis of battery aging and its impact on environmental impacts reveal that while larger batteries can slightly extend vehicle lifespan, the environmental gains are not always proportional to the added material and manufacturing impacts. For BEVs, increasing battery size tends to raise GWP per kilometer, as the additional production burden outweighs the modest gains in lifetime. In contrast, PHEVs benefit more from increased electric driving with larger batteries, which can reduce use-phase emissions, particularly in low-carbon contexts like France.

References

A2MAC1 (2023) Automotive Benchmarking: xEV Powertrain: Battery Cell Analysis. A2MAC1: Boulogne-Billancourt, France

ADAC (2022) Allgemeiner Deutscher Automobil-Club, VW Golf GTE DSG: technical data. URL https://www.adac.de/rund-ums-fahrzeug/autokatalog/marken-modelle/vw/golf/viii/314295/#motor-und-antrieb

Öivind Andersson, Börjesson P (2021) The greenhouse gas emissions of an electrified vehicle combined with renewable fuels: Life cycle assessment and policy implications. AE 289:116621, DOI https://doi.org/10.1016/j.apenergy.2021.116621, URL https://www.sciencedirect.com/science/article/pii/S0306261921001562

André M (2004) The artemis european driving cycles for measuring car pollutant emissions. Science of The Total Environment 334-335:73–84, DOI https://doi.org/10.1016/j.scitotenv.2004.04.070, URL https://www.sciencedirect.com/science/article/pii/S0048969704003584, highway and Urban Pollution

Bouter A, Hache E, Ternel C, Beauchet S (2020) Comparative environmental life cycle assessment of several powertrain types for cars and buses in france for two driving cycles: "worldwide harmonized light vehicle test procedure" cycle and urban cycle. IJLCA 25, DOI https://doi.org/10.1007/s11367-020-01756-2

Broussely M, Herreyre S, Biensan P, Kasztejna P, Nechev K, Staniewicz R (2001) Aging mechanism in li ion cells and calendar life predictions. J Power Sources 97–98:13 – 21, DOI https://doi.org/10.1016/S0378-7753(01)00722-4, URL http://www.sciencedirect.com/science/article/pii/S0378775301007224, proceedings of the 10th International Meeting on Lithium Batteries

Dai Q, Kelly JC, Dunn J, Benavides PT (2018) Update of bill-of-materials and cathode materials production for lithium-ion batteries in the greet® model. ANL

Dai Y, Liu X, Li H, Liu X, Zhang T, Su Z, Zhao S, Zhou Y (2025) Building-related electric vehicle charging behaviors and energy consumption patterns: An urban-scale analysis. Transportation Research Part D: Transport and Environment 141:104663

Das PK, Bhat MY, Sajith S (2024) Life cycle assessment of electric vehicles: a systematic review of literature. Environmental Science and Pollution Research 31(1):73–89

Dauphin R, Prevost V, Degeilh P, Melgar J, Fittavolini C, Smith A, Callu C, Chrysafi S, Uitz-Choi R, Kar K (2023) Evaluation of plug-in hybrid vehicles in real-world conditions by simulation. Transportation Research Part D: Transport and Environment 119:103721

DLR (2019) Deutsches zentrum für luft- und raumfahrt e.v. internal data. stuttgart.

Ehrenberger S, Philipps F, Konrad M (2019) Analysis of pollutant emissions of three plug-in hybrid electric vehicles. URL https://elib.dlr.de/128783/

Follmer R (2023) Mobilität in deutschland - mid ergebnisbericht. Tech. rep., Studie von infas, DLR, IVT und infas 360 im Auftrag des Bundesministers für Verkehr und digitale Infrastruktur (FE-Nr. 70.904/15). Bonn, Ber, URL http://www.mobilitaet-in-deutschland.de/

Fraunhofer (2022) Total net electricity generation in germany in 2022, (https://www.energy-charts.info/, section: Energy > pie charts on electricity generation > sources : Total > interval : year). URL https://www.energy-charts.info/charts/energy_pie/chart.htm?l=en&c=DE&interval=year&year=2022&source=total

Fröhlich M (2019) (deutsches zentrum für luft- und raumfahrt): Personal communication. stuttgart

Hasselwander S, Meyer M, Österle I (2023) Techno-economic analysis of different battery cell chemistries for the passenger vehicle market. Batteries 9(7), DOI 10.3390/batteries9070379, URL https://www.mdpi.com/2313-0105/9/7/379

Hawkins T, Singh B, Majeau-Bettez G, Strømman A (2013) Comparative environmental life cycle assessment of conventional and electric vehicles. JIE 17, DOI https://doi.org/10.1111/j.1530-9290.2012.00532.x

Helms H, Jöhrens J, Kämper C, Giegrich J, Liebich A, Vogt R, Lambrecht U (2015) Weiterentwicklung und vertiefte analyse der umweltbilanz von elektrofahrzeugen. ifeu - institut für energie- und umweltforschung heidelberg gmbh, umwelt-bundesamt. Tech. rep., DLR

Hoag K, Dondlinger B (2016) Vehicular Engine Design. Springer Vienna, DOI https://doi.org/10.1007/978-3-7091-1859-7

Houbbadi A, Redondo-Iglesias E, Pelissier S, Trigui R, Bouton T (2021) Smart charging of electric bus fleet minimizing battery degradation at extreme temperature conditions. pp 1–6, DOI https://doi.org/10.1109/VPPC53923.2021.9699367, 2021 IEEE Vehicle Power and Propulsion Conference (VPPC)

Huijbregts MAJ, Steinmann ZJN, Elshout PMF, Stam G, Verones F, Vieira M, Zijp M, van Zelm AHR (2017) Recipe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. IJLCA DOI https://doi.org/10.1007/s11367-016-1246-y

Jeanneret B, Redondo-Iglesias E, Trigui R, Vinot E (2010) Vehlib. URL https://gitlab.univ-eiffel.fr/eco7/vehlib

Kannangara M, Bensebaa F, Vasudev M (2021) An adaptable life cycle greenhouse gas emissions assessment framework for electric, hybrid, fuel cell and conventional vehicles: Effect of electricity mix, mileage, battery capacity and battery chemistry in the context of canada. JCP 317:128394, DOI https://doi.org/10.1016/j.jclepro.2021.128394, URL

https://www.sciencedirect.com/science/article/pii/S095965262102607X
Kosmidis I (2025) The impact of electric cars on travel behaviour segments: Insights from norway. Transportation Research Part D: Transport and Environment 142:104703
Lombardi L, Tribioli L, Cozzolino R, Bella G (2017) Comparative environmental assessment of conventional, electric, hybrid, and fuel cell powertrains based on lca. IJLCA 22, DOI https://doi.org/10.1007/s11367-017-1294-y
Marx SA Josefine and, Zapp P, Walachowicz F (2018) Comparative life cycle assessment of ndfeb permanent magnet production from different rare earth deposits. ACS SCE 6, DOI 10.1021/acssuschemeng.7b04165
Meteociel (2022) https://www.meteociel.fr/climatologie/obs_villes.php. URL https://www.meteociel.fr/climatologie/obs_villes.php
Mutel C (2017) Brightway: An open source framework for life cycle assessment. Journal of Open Source Software 2(12):236, DOI 10.21105/joss.00236, URL https://doi.org/10.21105/joss.00236
Nordelöf A (2019) A scalable life cycle inventory of an automotive power electronic inverter unit—part ii: manufacturing processes. IJLCA 24:694–711, DOI https://doi.org/10.1007/s11367-018-1491-3
Nordelöf A, Tillman AM (2018) A scalable life cycle inventory of an electrical automotive traction machine—part ii: manufacturing processes. IJLCA 23:295–313, DOI https://doi.org/10.1007/s11367-017-1309-8
Nordelöf A, Messagie M, Tillman AM, Ljunggren M, Van Mierlo J (2014) Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles—what can we learn from life cycle assessment? IJLCA 19, DOI https://doi.org/10.1007/s11367-014-0788-0
Patil TD (2024) Study of the environmental impacts of a plug-in hybrid electric vehicle (PHEV) in the context of optimal sizing and use. PhD thesis, Ecole Nationale des Travaux Publics de l'Etat [ENTPE], URL https://theses.hal.science/tel-05095369
Patil TD, Vinot E, Ehrenberger S, Trigui R, Redondo-Iglesias E (2023) Sensitivity analysis of battery aging for model-based phev use scenarios. Energies 16(4), DOI https://doi.org/10.3390/en16041749, URL https://www.mdpi.com/1996-1073/16/4/1749
Peters JF, Baumann M, Zimmermann B, Braun J, Weil M (2017) The environmental impact of li-ion batteries and the role of key parameters – a review. RSER 67:491–506, DOI https://doi.org/10.1016/j.rser.2016.08.039, URL https://www.sciencedirect.com/science/article/pii/S1364032116304713
Philip T, Whitehead J (2025) Consumer willingness to adopt electric vehicle smart charging: A stated preference analysis. Transportation Research Part D: Transport and Environment 146:104867
Redelbach M (2016) Entwicklung eines dynamischen nutzenbasierten Szenariomodells zur Simulation der zukünftigen Marktentwicklung für alternative PKW-Antriebskonzepte. DLR, Deutsches Zentrum für Luft- und Raumfahrt
Redondo-Iglesias E, Venet P, Pelissier S (2017) Eyring acceleration model for predicting calendar ageing of lithium-ion batteries. JES 13:176–183, DOI https://doi.org/10.1016/j.est.2017.06.009, URL https://www.sciencedirect.com/science/article/pii/S2352152X17300634
Redondo-Iglesias E, Vinot E, Venet P, Pelissier S (2019) Electric vehicle range and battery lifetime: a trade-off. Lyon, France, p 9p, URL https://hal.archives-ouvertes.fr/hal-02143273, 32 nd Electric Vehicle Symposium (EVS32), LYON, FRANCE, 19-/05/2019 - 22/05/2019
Shui B, Shafique M, Luo X (2024) Light-duty passenger vehicle electrification in china from 2021 to 2050 and associated greenhouse gas emissions: a dynamic fleet perspective. Transportation Research Part D: Transport and Environment 130:104199
Sjöqvist N, Ibrahem A (2021) Life cycle assessment in the automotive industry: Considerations for first-tier suppliers. Master's thesis, KTH Royal Institute of Technology
Song Z, Li J, Han X, Xu L, Lu L, Ouyang M, Hofmann H (2014) Multi-objective optimization of a semi-active battery/supercapacitor energy storage system for electric vehicles. Applied Energy 135:212 – 224, DOI https://doi.org/10.1016/j.apenergy.2014.06.087, URL http://www.sciencedirect.com/science/article/pii/S0306261914008964
Spotnitz R (2003) Simulation of capacity fade in lithium-ion batteries. J

Power Sources 113(1):72 – 80, DOI 10.1016/S0378-7753(02)00490-1, URL http://www.sciencedirect.com/science/article/pii/S0378775302004901

Szilágyi A, Bereczky A (2018) Comparison of the environmental impacts of a plug-in hybrid and a full electric car using life cycle assessment. JKONES 25(2):363–369

Xiong S, Ji J, Ma X (2019) Comparative life cycle energy and ghg emission analysis for bevs and phevs: A case study in china. Energies 12(5), DOI 10.3390/en12050834, URL https://www.mdpi.com/1996-1073/12/5/834

Xiong S, Wang Y, Bai B, Ma X (2021) A hybrid life cycle assessment of the large-scale application of electric vehicles. Energy 216:119314, DOI https://doi.org/10.1016/j.energy.2020.119314, URL https://www.sciencedirect.com/science/article/pii/S036054422032421X

Xu F, Crawford C, Feng Y, Lin Z, Li S (2023) Environment-economic analysis of diesel, hybrid electric, plug-in hybrid electric trucks in china. Transportation Research Part D: Transport and Environment 117:103661, DOI https://doi.org/10.1016/j.trd.2023.103661

Yang L, Yu B, Yang B, Chen H, Malima G, Wei YM (2021) Life cycle environmental assessment of electric and internal combustion engine vehicles in china. JCP 285:124899, DOI https://doi.org/10.1016/j.jclepro.2020.124899, URL https://www.sciencedirect.com/science/article/pii/S095965262034943X

Zhang Y, Cao Z, Zhang C, Chen Y (2024) Life cycle assessment of plug-in hybrid electric vehicles considering different vehicle working conditions and battery degradation scenarios. Energies 17(17), DOI 10.3390/en17174283, URL https://www.mdpi.com/1996-1073/17/17/4283

Zhu L, Shang WL, Wang J, Li Y, Lee C, Ochieng W, Pan X (2024) Diffusion of electric vehicles in beijing considering indirect network effects. Transportation Research Part D: Transport and Environment 127:104069