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The impact of lightweighting and battery technologies on the sustainability of electric vehicles: A comprehensive life cycle assessment

Omidreza Ahmadzadeh [a], Renato Rodriguez [a], Jonah Getz [a], Samy Panneerselvam [b], Damoon Soudbakhsh [a,*]

[a] Department of Mechanical Engineering, Temple University, Philadelphia, PA 19122, USA
[b] Caresoft Global Technologies, Inc. Livonia, MI 48150, USA

A R T I C L E I N F O

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A B S T R A C T

We present a comprehensive analysis of the greenhouse gas (GHG) emissions of two battery electric vehicles (BEVs) using detailed teardown data and contrast them with those of four internal combustion engine vehicles (ICEVs). We used the teardown data to calculate the production and recycling phases as well as for the vehicle dynamics modeling and estimating the utilization phase GHGs. After validating the models and establishing a baseline, we analyzed the effect of new trends on their net carbon footprint. Specifically, we considered lightweighting, battery technology, and charging technologies and showed the tradeoff between longer-range BEVs and their sustainability as a green alternative to ICEVs. The GHGs were calculated based on a life cycle assessment, including the vehicles' production, utilization, and disposal/recycling life. The GHGs of the production phase were calculated using detailed vehicle teardown data rather than general assumptions about the vehicles' material composition. Similarly, the utilization phase GHGs were estimated by first creating accurate dynamic models of the vehicles and validating them against vehicle test data. Then, we analyzed the effect of charging type and electricity source on the sustainability of these technologies. These studies showed that the average (mixed) US electricity source accounts for about 50 % of GHGs, and changing charging from household to station or supercharging can save about 8 % of GHG emissions. Next, we studied the effect of battery technology and lightweighting on EVs' net GHGs. OEMs have exploited both of these options to reduce the car's weight and improve its electrical consumption during the utilization phase (driving). Our study showed that while the higher energy density of battery technologies like NMC and NCAs is attractive for reducing the vehicle's weight and increasing its range, the use of rare materials significantly increases GHG emissions during production. Similarly, we showed that lightweighting by substituting steel with aluminum alloys (such as giga-casting) adds more production GHGs that significantly offset the savings in electrical consumption achieved during the vehicle's lifetime. Therefore, this study proposes three pivotal considerations in the design and utilization of electric vehicles: battery material selection, trade-off analysis for vehicle lightweighting, and adoption of efficient charging methods and energy sources, all of which aim to reduce their overall global carbon footprint.

1. Introduction

This research provides a framework for accurately modeling and estimating electric vehicles' carbon footprint. We show the effect of parameters such as house charging, electricity source, and the driving scenarios on electric vehicles' greenhouse gas (GHG) emissions. Moreover, our research highlights three key considerations for reducing the carbon footprint of electric vehicles across their production and usage phases. Drawing from a life cycle perspective, these principles enable various stakeholders, including designers, policy-makers, vehicle manufacturers, and their material and component suppliers, to assess the inherent trade-offs within these intricate systems.

Human activities are responsible for the increase in greenhouse gases (GHGs). GHGs are making the earth warmer as they trap heat. Transportation is the most significant contributor to this increase. The largest source of greenhouse gas emissions is from burning fossil fuels for electricity, heat, and transportation, with transportation accounting for 27 % of all GHGs in the USA in 2020 (EPA, 2023). Therefore, any new

* Corresponding author at: 1947 N. 12th St., Temple University College of Engineering, DSLab, Philadelphia, PA, USA.
E-mail address: damoon.soudbakhsh@temple.edu (D. Soudbakhsh).

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technology in the transportation sector, such as electric vehicles, should be evaluated for their GHG emissions. Life Cycle Assessment (LCA) is an important tool in sustainable engineering. It is used in the automotive industry and various other sectors to understand and mitigate the environmental impacts of products and processes (Xia and Li, 2022; Ellingsen et al., 2016; Mayanti, 2024; Elgowainy et al., 2016). LCA involves a detailed analysis of the inputs (e.g., energy, materials) and outputs (e.g., emissions, waste) at each stage. Environmental impacts are assessed across various categories, such as greenhouse gas emissions, air and water pollution, energy consumption, and resource depletion. The results of an LCA identify areas where improvements can be made to reduce a vehicle's environmental impact. They can also be used to compare different types of vehicles (e.g., internal combustion engine vs. electric) or different manufacturing processes to determine which options are more environmentally friendly.

The most important component in analyzing the GHGs of Electric Vehicles (EVs) and especially Battery Electric Vehicles (BEVs) is the emission during production, primarily due to the production of the batteries (Ambrose et al., 2020; Dunn et al., 2014). Li-ion batteries are among the most preferred battery types for EVs due to their high energy, power density, and long lifetime (Zubi et al., 2018; Karimi and Li, 2013). There have been efforts to improve their performance and modeling for EV applications (Zhang et al., 2019; Han et al., 2015; Moura et al., 2017; Park et al., 2021; Zhao et al., 2021; Park et al., 2018; Ecker et al., 2015; Ahmadzadeh et al., 2022). Battery recycling and refurbishment have the potential to reduce further the carbon footprint of EVs (Koroma et al., 2022; Nealer and Hendrickson, 2015; Sato et al., 2019).

While BEVs can run on renewable energies for their entire operation life, their production is not very environmentally friendly. It necessitates a more thorough analysis of transportation electrification and the steps for net-zero emissions (Sato et al., 2019; Ou et al., 2012; Onat and Kucukvar, 2022; Smith et al., 2017). While the production emissions constitute less than 10 % of the total emissions for conventional internal combustion engine vehicles (ICEVs), they make up approximately 40 % for a BEV (Ambrose et al., 2020). Moreover, if the BEVs operate with renewable energies, this number is equal to two-thirds of the total emissions of BEVs. For example, the extra production emissions generated by a Tesla Model 3 Standard Plus are roughly equivalent to the sum of the emissions of production of a Volkswagen Passat 2.0 TSI and driving 18,000 km (Buberger et al., 2022). Adding to this number, electrifying may not be sufficient if the utilization phase energy is not renewable, and the transport will not greatly impact the environment (Gustafsson et al., 2021; McLaren et al., 2016). This leads to other studies suggesting a hybrid vehicle could be a better alternative due to the smaller-sized batteries (Andersson and Börjesson, 2021; Elgowainy et al., 2009; Ternel et al., 2021). However, most of the studies on the LCA analysis of the EVs rely on the secondary data as opposed to the primary data (Temporelli et al., 2020). In this study, we use accurate teardown data to obtain a more complete picture of the emissions of the vehicles.

The key contributions of this research are: i) including detailed material and teardown data to calculate the carbon footprint of BEVs, providing a more accurate analysis compared to studies relying on generalized assumptions about vehicle material composition; ii) developing accurate dynamic models and validating them using Environmental Protection Agency (EPA) test data for the Utilization Phase modeling; (iii) comparing the LCA of BEVs with ICEVs within the same vehicle class and similar mass, utilizing the average GHG emission from vehicle productions and detailed teardown data. Assessing the break-even points between BEVs and ICEVs and evaluating long-term environmental impact; and iv) introducing critical considerations from a life cycle perspective in the design and utilization of electric vehicles to lower their carbon footprint and enable stakeholders to evaluate the inherent trade-offs within these complex systems. Our proposed considerations include: 1) Prioritizing cleaner battery technologies like LFP batteries over NMC and NCA materials, potentially saving up to 30 % of battery production emissions. 2) Conducting a comprehensive analysis of lightweighting, particularly when substituting steel with aluminum. While aluminum and giga-casting processes can enhance range and utilization efficiencies, the increased carbon footprint during production significantly offsets the savings over the car's lifespan. 3) Adapting station charging instead of home charging to achieve significantly higher charging efficiency.

The electric vehicles examined in this study encompass the 2017 Tesla Model 3 Long Range and the 2021 Volkswagen ID.4. Nevertheless, our findings reveal broader trends within the realm of electric vehicles and battery technology that extend beyond these specific models.

2. Life cycle assessment (LCA)

Life Cycle Assessment (LCA) is a methodology used to evaluate a vehicle's environmental impacts throughout its life cycle (Xia and Li, 2022; Ellingsen et al., 2016; Mayanti, 2024; Akhshik et al., 2017). LCA analysis includes all stages of the vehicle's life, from the extraction of raw materials used in its production and manufacturing of the parts to the vehicle's utilization, maintenance, disposal, and recycling as shown in Fig. 1. Through this analysis, we can determine the environmental footprint of each vehicle for comparative studies. In this section, we discuss the analysis and assumptions for calculating the cycle life.

Typically, GHG emissions of different greenhouse gases are quantified in terms of equivalent CO_2 emissions, and the total emissions, E_{total}, are a sum of the emissions during the life cycle of the vehicles as follows:

$$E_{\text{total}} = E_{\text{prod}} + E_{\text{util}} + E_{\text{disp}}, \tag{1}$$

where $E_{\text{prod}}, E_{\text{Util}}$, and E_{disp} are the emissions during production, utilization, and disposal and recycling of the vehicle, respectively. In what follows, we discuss the calculations of each term.

2.1. Production phase

The Production phase emissions can be calculated based on the emissions of the following categories:

Raw Material Extraction and Processing: This phase involves the extraction of raw materials such as stainless steel, aluminum, plastics, and rubber, as well as the processing of these materials to create components like the body-in-white (BIW), batteries, and Electric motors. The data from this part is extracted based on a detailed teardown of the vehicles from the Iceberg database (Iceberg, 2023).

Manufacturing, Assembly, and Distribution: This phase encompasses the production of the vehicle, including the assembly of various components and subsystems, as well as the transport of the vehicle components to assembly plants and the vehicle to the customers. The analysis uses a standard calculation offered by GREET (The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model Rev.2023) (GREET: The Greenhouse Gases, 2019; Burnham et al., 2006) to estimate the GHGs from these processes.

Vehicle Operation and Maintenance: This includes the energy consumption, emissions, and other environmental impacts associated with using the vehicle during its operational life, including fuel consumption, emissions of pollutants, and maintenance activities.

End-of-Life: This stage encompasses the vehicle's disposal, recycling, or reuse and its components after it is no longer used. This can include processes such as dismantling, shredding, and recycling of materials.

2.1.1. Production emissions of the vehicle body and components

We used GREET (GREET: The Greenhouse Gases, 2019; Burnham et al., 2006) to calculate the GHGs associated with car production. The GREET model conducts separate calculations for each material, and the extraction material's processing is then simulated through one or more stages. We made an effort to maintain the distinction between

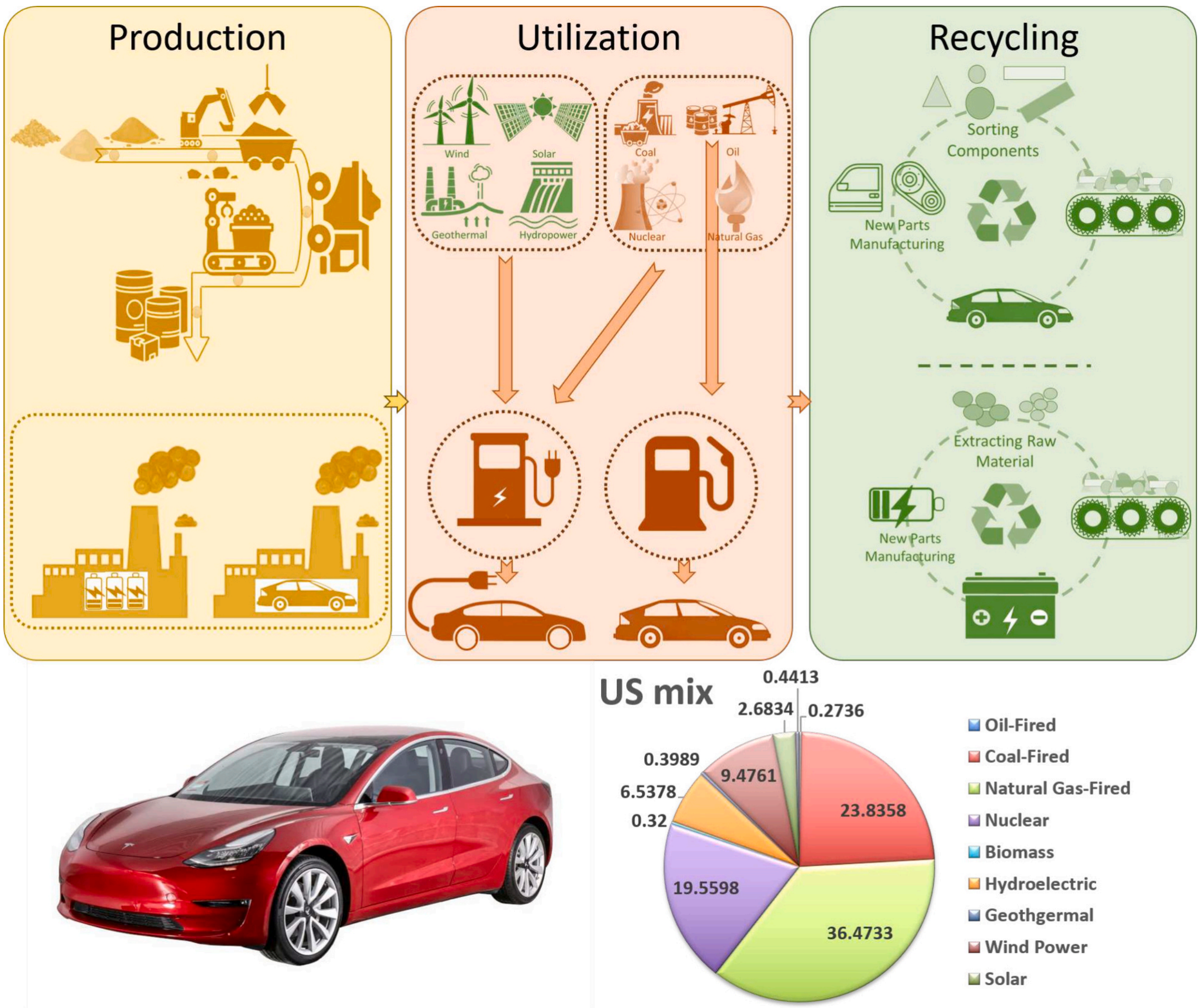


Fig. 1. LCA Analysis involves estimating GHGs throughout the vehicle's life (Production, Utilization, Disposal, and Recycling) and considering the location (and source of energy) where the vehicle is manufactured and operated.

production stages and, when feasible, introduced additional intermediary steps into the model. However, this was only sometimes achievable due to how industry data is compiled, potentially resulting in a loss of detail. The primary geographical focus of the data is North America. Global data was also incorporated when necessary to fill in any data gaps. The material data was extracted from detailed teardown car data of the Iceberg library. The data includes material properties and weights of each component, including doors, trims, body in white (BIW), transmission, glass, etc., and we use the following equation to calculate the emission of the vehicle body (excluding the battery pack):

$$E_{\text{prod,body}} = \sum_i m_i E_i \tag{2}$$

where m_i is the weight of each part and E_i is the emission of the material composition and processing of the material that depends on the full production pathway. For example, the body-in-white has parts with Aluminum alloys with different processes, such as casting or from sheet metal, with subcategories such as cold and hot rolling. Then, the emission of each part was calculated as the product of the weight of the part and the associated emission of the material and processing. We note that the calculations include the scrap material and the material that typically comes from recycled components.

Another consideration in the production phase emissions is the number of times a specific part needs to be changed over the life of a vehicle. Examples of such components are the oils, liquids, and tires. For example, we considered changing them every 50,000 km. We note that older tires reduce the vehicle's fuel efficiency during the use phase.

2.1.2. *Production emissions of the battery packs*

The battery pack is a major contributor to the BEV total emissions, and the carbon footprint of battery packs can be divided into three categories (Crenna et al., 2021): Cell production, which includes cathode production (mainly: cathode slurry production, Cathode precursor (oxide) production), anode production, and pack assembly. We include all three in our analysis. Another consideration in this study is the region of the manufacturing of the cells as they impact the results (Winjobi et al., 2022). For example, for the NMC811 (Nickel Manganese Cobalt) cathode of the cells, the GHGs are in the range of 1.21 times to 3.47 times the baseline values in the GREET due to the changes in the supply chain (Winjobi et al., 2022). We represent the total production emissions of the vehicle E_{prod} as

$$E_{\text{prod}} = E_{\text{prod,body}} + E_{\text{battery}} \tag{3}$$

where E_{battery} is the total emissions used in the production and assembly of the battery packs.

2.2. Emissions from assembly, disposal, and recycling

Assembly, Disposal, and Recycling (ADR) is a framework that emphasizes responsible and sustainable practices in the lifecycle of products, from their creation (assembly) to their end-of-life management (disposal and recycling). ADR is an initiative to encourage product designs with recycling in mind and implement efficient and environmentally friendly disposal practices. Here's what each component of ADR refers to: I) Assembly: This refers to assembling various components or parts to create a finished product; the typical vehicle assembly process involves several key steps, including painting, HVAC installation, material handling, welding, and compressed air supply. ii) Disposal: This involves disposing of no longer useful products that have reached the end of their life cycle; and iii) Recycling: This is converting waste materials into reusable materials. ADR helps conserve resources and reduce the environmental impact of waste, and the GREET model factors the energy use of materials associated with recovering specific recycled materials. In this study, we separate the vehicle's ADR from the battery assembly and include its separate calculations in the battery packs' production emissions.

2.3. Utilization phase modeling

The utilization phase is related to the vehicle's daily operations and commutes. Therefore, a dynamic model is required to estimate the energy utilization and wear and tear. The main parameters affecting the dynamic response of the BEVs are the aerodynamic forces, rolling resistance of the tires, high-voltage battery, powertrain, and driving cycles, as shown in Fig. 2.

We analyzed the utilization phase energy consumption and GHGs using Autonomie (Autonomie, 2024), which allows for simulating vehicle systems employed in evaluating the energy usage, effectiveness, and expenses associated with various cutting-edge vehicle technologies spanning a range of classes (from light to heavy-duty), powertrain options like electric vehicles, components, and control methodologies. Within Autonomie, vehicle control algorithms are derived from extensive vehicle dynamometer tests encompassing numerous powertrain setups. Furthermore, Autonomie grants complete accessibility to the component models and control algorithms. Fig. 3 provides an overview of the vehicle modeling configuration within Autonomie. The motor power and efficiencies were found from (*Performance Analysis of the Tesla Model 3 Electric Motor using MotorXP-PM, Tech. rep., VEPCO Technologies, Inc., CHINO, CA, USA*, 2020), where peak power and peak torque of 430 Nm and 192 kW were used. The phase current is 1000 ARMS under 94.6 VRMS, which translates to 231 Vdc minimum bus voltage. We modeled the total available power by modeling the battery packs as individual cells connected in series and parallel (for example, Tesla has a cell arrangement of 46×96).

Table 1 shows the higher-level parameters of the cars of this study.

Reducing the aerodynamic drag forces, f_d is crucial for increasing the range of EVs, especially for highway driving, as it is proportional to the square of velocity, V, and relates to the frontal area of the vehicle, A_f, as in

$$f_d = \frac{1}{2}\rho c_d A_f V^2 \tag{4}$$

where c_d is the drag coefficient and ρ is the air density. We used c_d of 0.23 and 0.28 for Tesla Model 3 and VW ID4, respectively. Their respective frontal areas were calculated as $A_f = 2.2\ \mathrm{m}^2$ and $2.58\ \mathrm{m}^2$.

The required power consumption P_d from the drag force is given by:

$$P_d = f_d V \stackrel{\text{def}}{=} \frac{1}{2}\rho c_d A_f V^3, \tag{5}$$

The frontal area and drag coefficients are constant for each vehicle, and the power consumption increases with V^3. Electric motors lose efficiency at higher velocities; hence, reducing the frontal area and drag coefficient is more important in their design. Despite that, driving EVs at higher velocities requires more energy compared to city driving, which is in contrast to ICEVs and implies that driving at highway speeds leads to less efficient EV driving and more energy throughput (increased battery cycling).

Another important factor in high-speed and low-speed driving is the rolling resistance of the tires, which is the energy lost due to the deformation and hysteresis of the tire as it rolls. We used a second-order eq. (6) to represent the tire's rolling coefficient, c_r, as follows:

$$c_r = c_{r1} + c_{r2} V \tag{6}$$

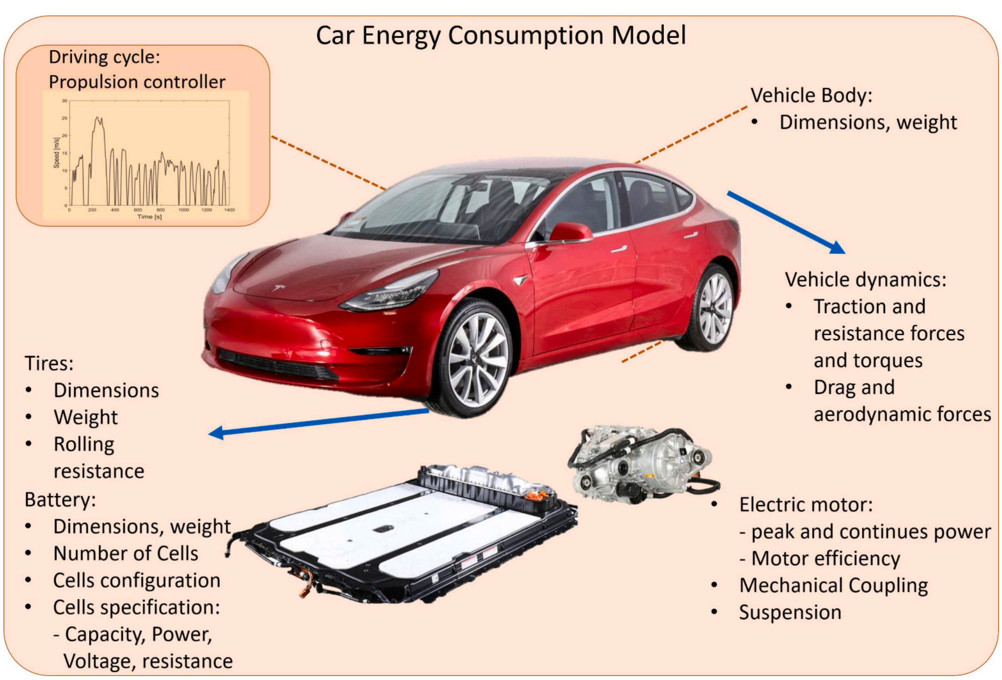


Fig. 2. Utilization phase Modeling includes creating a dynamic vehicle model, including the powertrain, and defining appropriate driving scenarios.

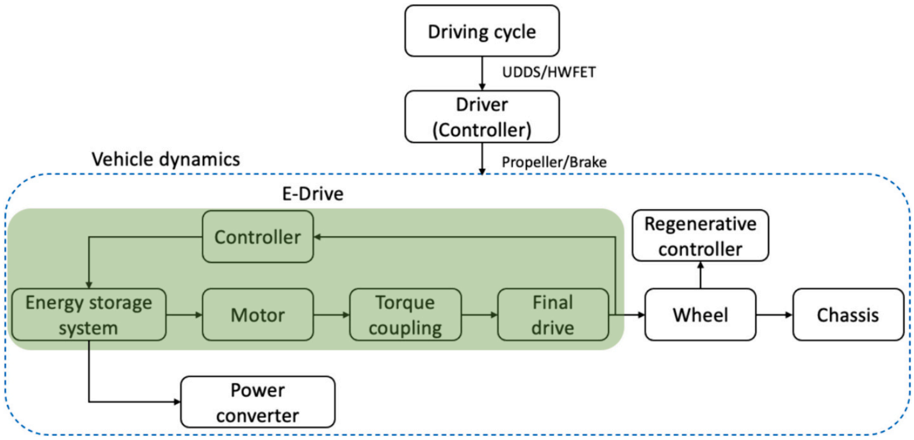


Fig. 3. Configuration of vehicle modeling in Autonomie.

Table 1
Comparison of the two modeled vehicles.

Parameter	Tesla 3LR	VW ID.4	Unit
Weight	1769	2128	kg
Wheelbase	2875	2766	mm
Trackwidth (average)	1580	1576	mm
Battery Shape	Cylindrical cell	Pouch cell	–
Cells	4416	288	cells
Pack Power	75	82	kWh
Motor Power	202	150	kW

where c_{r1} is the constant coefficient and c_{r2} shows the velocity dependency of the coefficient.

3. Results

In this study, we created and analyzed two electric vehicles: the Tesla Model 3 Long Range, 2017, and the Volkswagen ID., 2021. We used 200,000 km as the total life of BEVs in this study, which we discussed in section 3.2.2.

3.1. Production and end-of-life phase

We used the detailed teardown of the vehicles from the Iceberg Library. Fig. 4 shows the greenhouse gases produced during the production of these cars. These electric vehicles generally have much higher production GHGs than their ICEV counterparts. This is mainly due to the production and assembly of the batteries, as shown in the figure. Furthermore, they use more Aluminum than conventional vehicles, refer to § 4.5, increasing their carbon footprint during production.

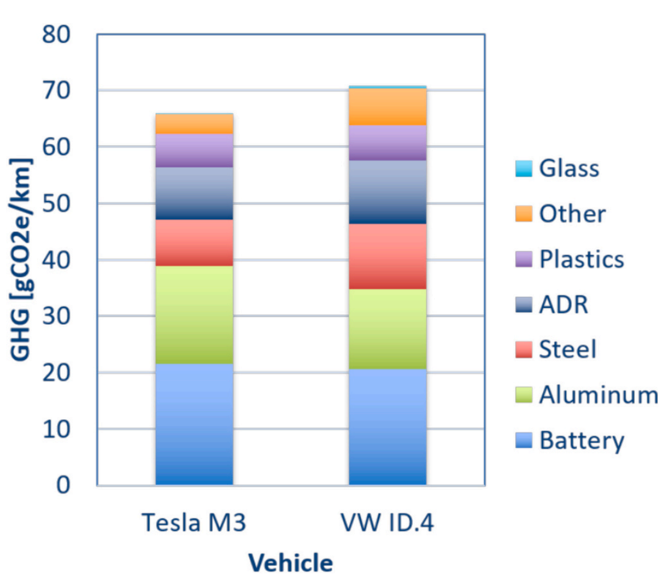


Fig. 4. The GHGs of the selected electric vehicles.

Also, the analysis shows that the share of battery production and assembly is about 34 % for Tesla Model 3 LR, 2017, and 30 % for Volkswagen ID.42021. This number is equal to driving an average car with 8 L/100 km fuel consumption for about 21,500 km.

The ADR section includes the end-of-life phase, which represents the assembly, disposal, and material recycling processes. This phase is critical as it addresses the environmental impact of the product after its useful life. Additionally, during the production phase, a portion of materials, such as Aluminum, is sourced from recycled content. This means the effect of recycling materials from the end-of-life phase is already accounted for in the production phase. Consequently, the ADR section includes the GHG emission associated with the recycling process, while the GHG reduction from using recycled materials is included in the production phase of materials.

3.2. Utilization phase modeling

The dynamic response of each car was modeled by incorporating several key car parameters and comparing them with the results of the Environmental Protection Agency (EPA) test. The models were created to simulate and analyze their performance characteristics. The inputs crucial to this simulation encompass a range of factors, including the drag coefficient, which represents the aerodynamic resistance the vehicle encounters as it moves through the air. Additionally, tire properties are pivotal in determining the car's energy consumption. The *E*-Drive system, a cornerstone of electric vehicles, encompasses components like the electric motor and powertrain. The electric motor is the prime mover, converting electrical energy stored in the vehicle's battery into mechanical energy to drive the wheels. We determined the motor and parameters based on published data (Wassiliadis et al., 2022). Another crucial factor in EV modeling is the high-voltage (HV) battery, the primary energy storage unit. The battery's capacity and efficiency impact the vehicle's range and overall performance. Finally, the drag forces from the rolling resistance of the tires (Wargula et al., 2019) and the vehicle's aerodynamics are crucial for the modeling, and they impact the vehicle's performance, especially at higher speeds. In summary, when modeling a car, taking into account these inputs—drag coefficient, tire properties, E-Drive components like the electric motor and powertrain, the high-voltage battery, and factors affecting drag—allows for a comprehensive simulation that reflects the vehicle's behavior and performance in real-world conditions.

3.2.1. Driving profiles

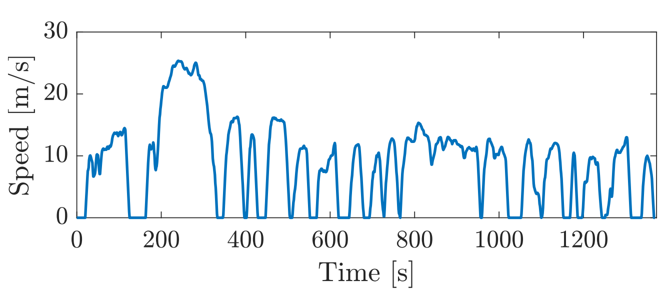
In this study, we used standard driving profiles by the EPA. These driving cycles encompass a variety of factors, such as speed, acceleration, deceleration, and idling times, providing a comprehensive snapshot of how a vehicle is driven in real-world scenarios. Specifically, we used UDDS (Urban Dynamometer Driving Schedule) to emulate typical city driving conditions (see Fig. 5a) and the Highway Fuel Economy Cycle (HWFET) (see Fig. 5b) to simulate driving at higher speeds. Total driving is defined as HWFET driving followed by UDDS driving for a standard mix of city and highway driving. The driving cycles allow for the vehicle's operational conditions during a specific period. This data is crucial for evaluating the performance and efficiency of vehicles under different driving conditions. Efficinecy refers to the ratio of output energy (or power) to input energy (power) in a system. The simulated values are compared to the ones from the EPA test results, showing the accuracy of the responses. The adjusted values from the simulation with the efficiency of household charging are shown in Table 2. The error from the EPA test results for both cars was less than 1 %.

We note that validating the results allows for comparing the vehicles under different driving scenarios, such as more aggressive driving or using the European driving schedule (WLTP).

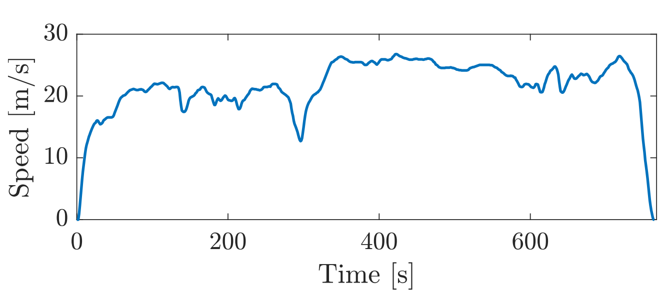
3.2.2. Total GHGs

The total carbon footprint of vehicles and savings from electrification depends on the life of the vehicles. The average life of passenger cars is about 244,000 km based on a study by NHTSA (National Highway Traffic Safety Administration) (Lu, 2006). However, there is no consensus on the life of EVs. Several parameters affect the life of EVs, such as the cycling life and degradations in the powertrain efficiency (Ellingsen et al., 2016), and researchers have used many different values such as 160,000 km (Kawamoto et al., 2019), 171,000 km (Elgowainy et al., 2016), 180,000 km (Ellingsen et al., 2016), and 200,000 km (Buberger et al., 2022). Many recent studies and OEMs tend to compare the ICEV and EVs using 200,000 km across the board for the vehicles. In our analysis, we used this number to be more consistent with the other studies and provide a short discussion about the effect of this number on the results.

We note that the choice of software and other calculation



(a) UDDS



(b) HWFET

Fig. 5. Driving profiles: a) UDDS for city driving, and b) HWFET for highway driving.

Table 2
Comparison of the simulated values to the EPA tests (utilization test).

Wh/km	Tesla 3LR	Volkswagen ID.4
UDDS: Simulated	160.1	201.5
UDDS: EPA	159.9	201.4
HWFET: Simulated	174.9	235.1
HWFET: EPA	174.5	235.3

assumptions influences the LCA assessments. In (Herrmann and Moltesen, 2015), the authors showed that the LCA results could be significantly different due to the underlying calculations. In this study, we used the GREET (The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation) Model (GREET: The Greenhouse Gases, 2019; Wang et al., 2023) for LCA assessment. Fig. 6 shows a breakdown of the GHG emissions of the studied BEVs throughout each phase of the LCA.

We compared the GHG emissions of the BEVs with two common ICEVs in the same vehicle class (the 2017 Chevrolet Malibu and the 2017 Honda Accord) and two ICEVs with similar mass (the 2020 Ford Escape and the 2020 Volkswagen Tiguan). For the production phase of the Malibu and Accord, we used the average emission of 4.56 kgCO2e per kg weight of the vehicle (Buberger et al., 2022). However, we utilized detailed teardown data for the Escape and Tiguan to calculate their production GHG emissions. In the utilization phase, we used EPA data for ICEVs fuel consumption, with each liter of gasoline emitting 2.3477 kgCO2e (OAR, 2016).

Fig. 7 shows a comparison of the LCA of these vehicles. While BEVs emit more GHG during production compared to ICEVs, their GHG emissions are lower during utilization. For example, after driving 50,000 km, the Malibu contributes more to GHG emissions than the Tesla Model 3. The breakeven point for the Accord and Tesla Model 3 is around 120,000 km, as the Accord is more environmentally friendly than the Malibu. Furthermore, the VW ID.4 produces more GHG than the Accord due to its classification as a crossover Sports Utility Vehicle (SUV) and consumes more energy than midsize vehicles for production. However, around 80,000 km, the Malibue emits more GHG than the VW ID.4. Similarly, both the Escape and Tiguan produced less GHG during production compared to BEVs, while their breakeven points are around 25,000 km and 35,000 km for the Tesla Model 3 and VW ID.4, respectively. This is attributed to the Escape and Tiguan classification as compact crossover SUVs, leading to higher fuel consumption compared to sedans like the Malibu and Accord.

4. Impact of different practices in EV production and usage

4.1. Effect of charging

Here, we analyze the effect of charging type efficiency on the GHGs of the vehicles, which reduces the carbon footprint from the baseline (household charging). For these calculations, we assume the average US electric mix represents the average electricity source for any type of charging. Also, while fast charging, particularly with static current profiles, can reduce the battery's cycle life, employing advanced and dynamic fast-charging current profiles can help decrease the degradation rate of the battery, thereby ensuring a longer cycle life (Abdel-Monem et al., 2017). Therefore, in this section, we ignore variations in the total GHG due to the effect of charging type on the battery life. Table 3 shows that a BEV's carbon footprint (in this case, Tesla Model 3, LR) decreases if the BEVs are charged via a station charging or supercharging (efficiency of about 90 %) compared to the household charging (efficiency of about 75.3 %). These values show the emissions per kilometer, and the main difference is coming from the inefficiencies of the charging technology. These improvements are consistent across different driving conditions, whether on highways or in city driving. Based on these results, investing in transforming household charging to a more advanced charging station reduces the carbon footprint of EVs by

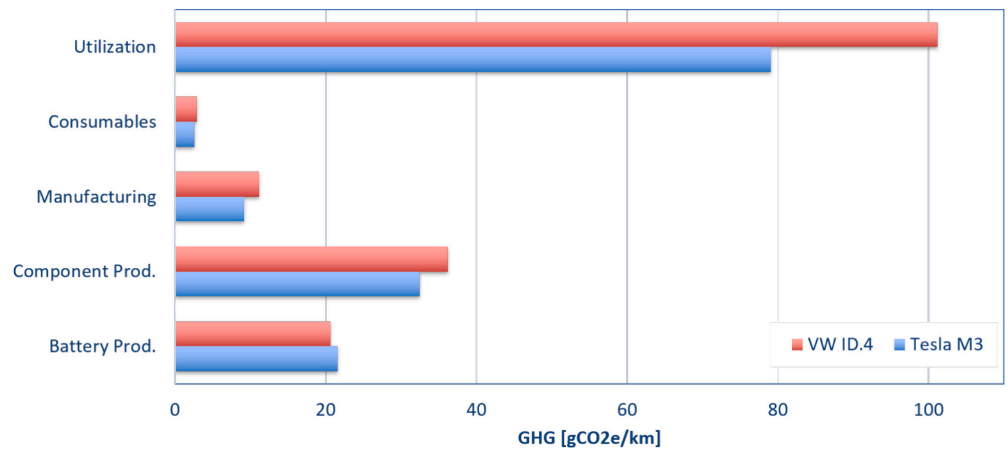


Fig. 6. Breakdown of the GHG emissions in each phase.

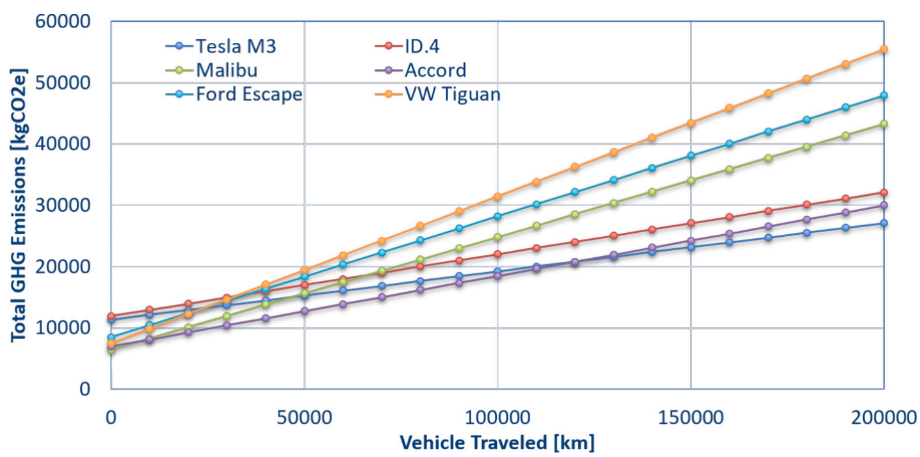


Fig. 7. Comparison of the total GHG emissions in the US for BEVs and ICEVs.

Table 3
Impact of charging efficiency on the GHGs of a BEV.

Charging Scenario [gCO2e/km]	HWFET	UDDS	US-Combined
Household (120v/12 A)	152.6	144.5	149.3
Charging station (240 v/12 A)	140.2	133.4	137.4
Super Charging	139.9	133.3	137.2

8 % while significantly reducing their charging time.

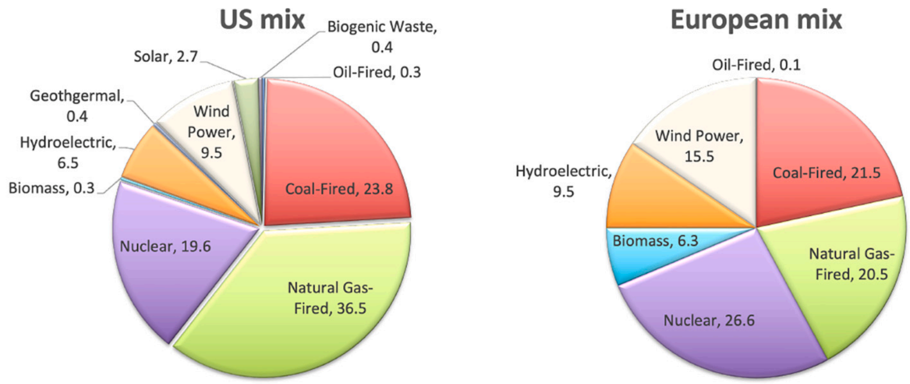
4.2. Effect of electricity source

This section investigates the effect of the location where the BEVs are operated based on the energy source. Fig. 8a shows the source of electricity in Europe vs. the US. This figure shows that while the US mix is comprised of over 36 % natural gas compared to about 20 % in the EU, the share of wind power is much more in the EU than in the US. As a result, the overall GHGs of driving an electric car are higher in the US than in Europe, as shown in Fig. 8b. This figure shows that the GHGs of a Tesla Model 3 LR are higher in the US in all driving scenarios. As expected, the total GHG emissions would be significantly reduced if the car used only renewable resources such as wind energy. The calculations are shown for station charging.

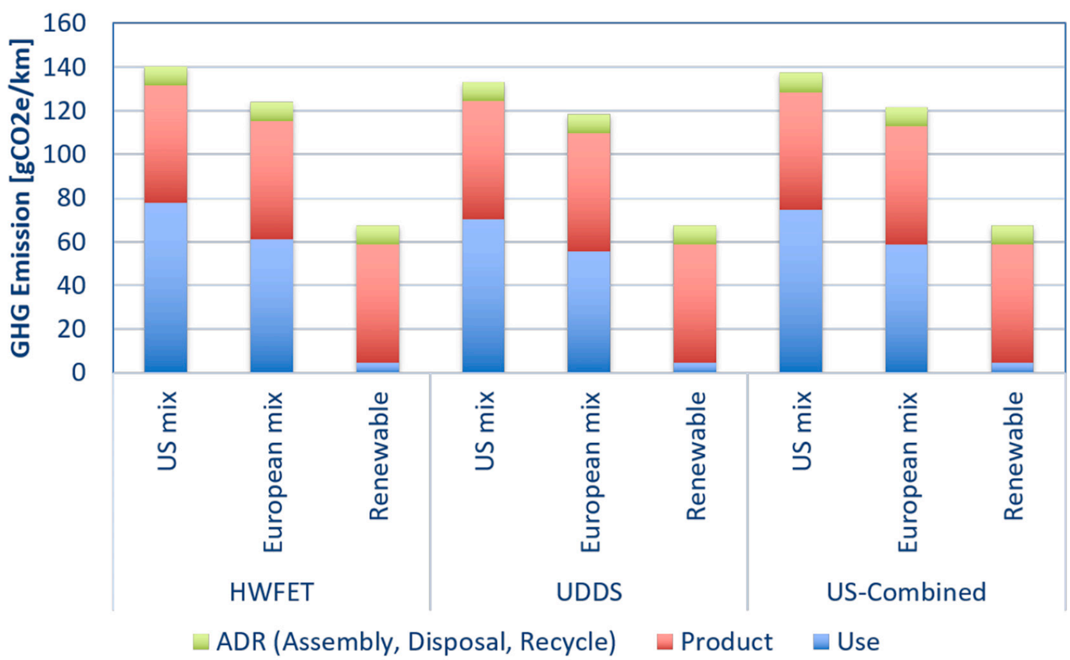
4.3. Effect of battery materials

Here, we analyze the impact of different battery technologies on the carbon footprint of electric vehicles. We showed that the GHG of the battery pack of Tesla Model 3 with Lithium Nickel Cobalt Aluminum Oxide (NCA) material is about 40 % of the total production of the vehicle. Similarly, the NMC battery material of ID4 contributes to about 35 % of its total material production. Therefore, reducing the carbon footprint of the battery pack significantly reduces the emissions of the vehicles. In this research, we considered three scenarios regarding the effect of battery technology, EV charging technology, and light-weighting via added aluminum. First, we compare the different Li-ion battery materials used in Tesla Model 3 production: Solid state Lithium Iron Phosphate (LFP), NCA, and NMC811. LFP, among the first commercialized Li-ion batteries, has a lower energy density than NCA (Placke et al., 2017). However, LFP is more environmentally friendly as it does not contain rare materials such as Cobalt, which is present in NCA and NMC811 (Xia and Li, 2022). We calculated the GHG emission of different battery types per Wh, with LFP producing 29.04 gCO2e/Wh, NCA producing 41.27 gCO2e/Wh, and NMC811 producing 42.24 gCO2e/Wh during production. Therefore, LFP significantly emits fewer GHGs than NCA and NMC, despite its lower energy density, and can reduce the GHG production of BEVs significantly. However, it is important to note that while LFP produces fewer GHGs, it is highly sensitive to temperature, and its performance degrades significantly in low temperatures.

We note that there are several constants in battery production, such as assembly and transportation. Fig. 9 displays the GHG emissions of primary materials for NMC811, NCA, and LFP per Wh. The active material is the largest contributor to GHG emission, and for LFP, since it



(a) Percntage of the US and EU sources of electricity



(b) GHGs

Fig. 8. Effect of electricity Source during the Utilization Phase: a) The US and European (EU) mixed electricity sources [%], and b) GHG dependency on the source of energy.

does not contain Cobalt, its emissions are lower than those of the other two battery types. Graphite and aluminum produce more GHG emissions than the active materials; however, their values are the same for all three battery types.

We note that several studies suggested shorter life for BEVs compared to the ICEVs (Ellingsen et al., 2016; Kawamoto et al., 2019), which would reduce the savings of the utilization phase. For example, in (Kawamoto et al., 2019), the authors suggested 160,000 km as the expected life of the BEVs. The rationale behind these numbers is the expected shorter life cycle of the battery packs compared to the traditional engines. Usually, the battery packs need to be replaced after 20–30 % loss of capacity from their nominal capacity, and as discussed in this study, battery production is a major contributing factor to the carbon footprint of BEVs. Therefore, the general consensus is to apply the LCA for EVs with one battery pack. Creating additional pathways for the batteries, such as using them in second-life applications (e.g., electricity grids), can further improve the overall sustainability of BEVs.

The calculated efficiencies assume ideal conditions and components. Both types of vehicles have components that degrade over time and reduce their efficiency. Particularly, the efficiency of new and properly inflated tires results in significantly more efficient driving. While some components in ICEVs, like lubricants and catalysts, can be easily replaced to maintain performance, other parts, such as cylinders and transmission systems, are costly to replace, leading to higher fuel consumption as the vehicle ages. This is similar to components of the EVs' drivetrain. In the next section, we investigate the drop in efficiency of BEVs due to the aging of the batteries, as this form of efficiency does not exist in ICEVs.

4.4. *Effect of battery aging*

This section examines the impact of battery aging on BEVs. The battery is the main energy source in BEVs, and its performance degrades over time, affecting overall vehicle performance. We analyze the life of

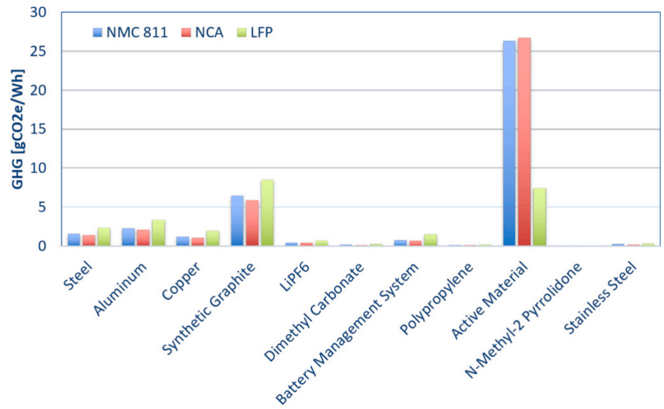


Fig. 9. Comparison of the GHG emissions per Wh for different battery materials during production.

multiple Li-ion battery chemistries, including LFP, NCA, NMC111, and NMC811, considering their use in a passenger car for daily commutes in city and highway conditions. Our driving profile is defined as follows:

Weekdays: EPA combined +8 h rest + EPA combined + remaining rest for the day.

Weekends: 4 EPA combined followed by charging profile from Blast and rest until Monday.

Here, the EPA combined driving cycle represents the sum of the UDDS and HWFET cycles. Fig. 10 displays the battery state of charge (SOC) over the specified drive cycles for one week. On the final day (Sunday), the battery remains fully charged, as the car is not used. According to the proposed driving scenario, the car drives over 26,000 km per year.

We use Battery Lifetime Analysis and Simulation Tool Suite (BLAST) (Smith et al., 2021; Preger et al., 2020; Brooker et al., 2015) to model battery aging during cycling and calendaring while accounting for temperature variations. To incorporate the impact of temperature on degradation, we use actual temperature data from Phoenix, AZ, representing hot weather, and Philadelphia, PA, representing cold weather, over one year (2018) (Sengupta et al., 2018) as shown in Fig. 11a.

Fig. 11b illustrates the relative discharge capacity fade of the three Li-ion battery chemistries, based on the cycling profile repetition shown in Fig. 10 for hot and cold climates. Battery chemistry significantly impacts the degradation. For example, NMC111 cells degrade more slowly compared to NMC811, which reaches 80 % of its initial capacity in less than 3.5 years. Furthermore, lower ambient temperatures

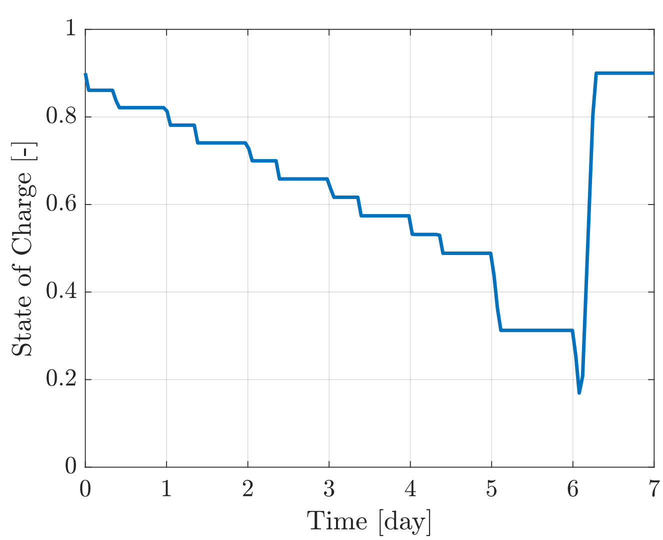


Fig. 10. Battery state of charge for the proposed drive cycle.

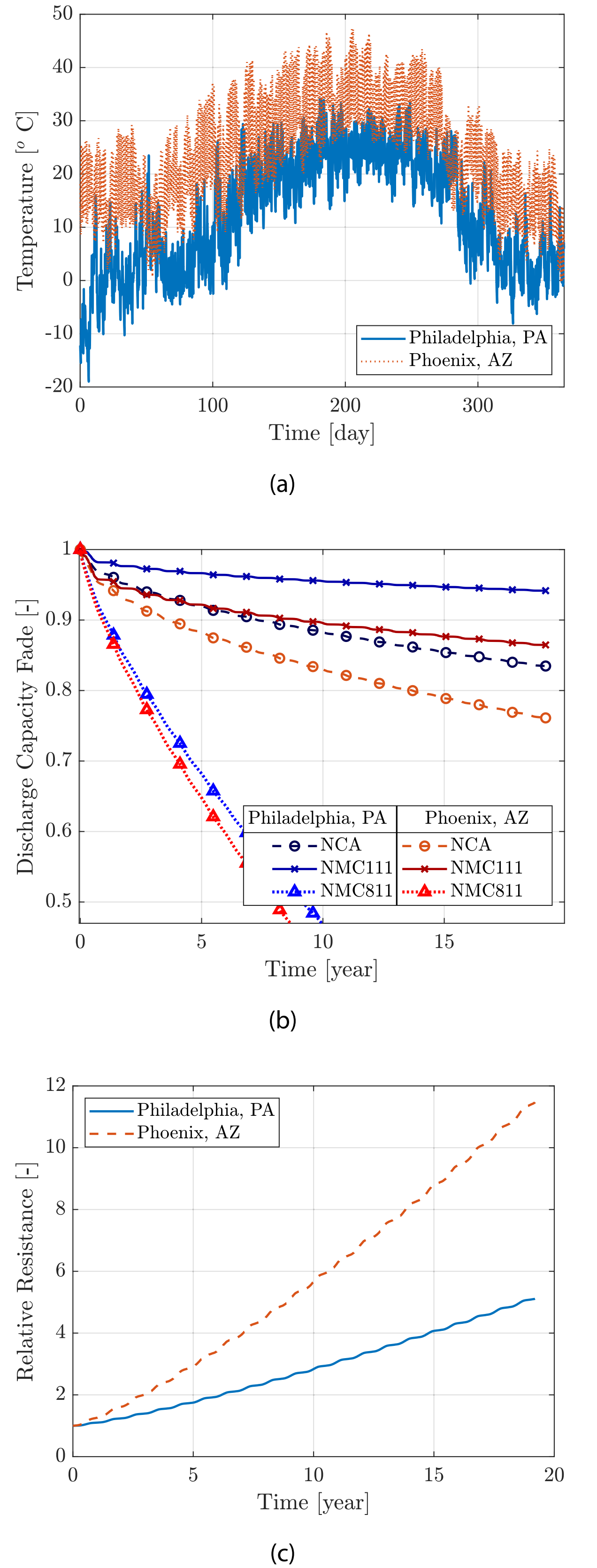


Fig. 11. a) Temperature data for two simulated cities, b) Battery capacity degradation over the vehicle's lifetime driving in different climates with the same scheduled driving scenario, and c) Increase in the relative resistance over time.

improve battery life, whereas cells degrade faster at higher temperatures (Mishra et al., 2020). As shown in Fig. 11b, NCA (Tesla Model 3 LR battery) reaches its useful life (20 % capacity degradation) in 13.7 years in Phoenix, AZ, while in Philadelphia, PA, NCA's capacity degrades to only 0.83 % after 20 years. We should note some limitations with these estimates: 1) the original experiments were conducted on single cells (Preger et al., 2020); hence, the adverse effects of imperfect cells on the rest of the cells in a battery module are not included in the study, and the modeling, which significantly reduces a batter module/pack's life, and 2) the experiments were conducted mainly at 15, 25, and 35°*C*. Hence, the battery life may vary with extended exposure to cold temperatures or depending on the quality of the batteries in a battery module.

Battery capacity fades, and ohmic resistance increases over time (Zou and Zhang, 2019), reducing the efficiency of BEVs. Similarly, the efficiency of ICEVs diminishes over time due to the wear and aging of their components (Baweja and Kumar, 2021; Wang et al., 2021). Fig. 11c displays the increase in relative resistance of an NMC111 cell over 20 years based on the proposed drive cycle in both hot and cold environments. As with degradation behavior, hot weather increases the battery's resistance more than cold weather, resulting in higher power consumption in BEVs.

4.5. Effect of lightweight materials in BEV production and utilization

This section examines the impact of the growing demand for advanced lightweight materials in the production of BEVs. The overwhelming majority of electric vehicles exhibit significantly greater weight compared to their gas-powered counterparts. For instance, BEVs from Ford, Volvo, and Toyota are approximately 33 % heavier than their equivalent gas-powered models (Homendy, 2023). The additional weight primarily stems from the sizable battery packs utilized in BEVs, leading to potential reductions in vehicle performance such as fuel economy and driving range (Jung, 2020). Moreover, the heightened weight raises safety apprehensions when considering that being struck by a vehicle with an additional 500 kg leads to a 40–50 % increase in the risk of fatalities (Anderson and Auffhammer, 2014).

The substitution of cast iron and conventional steel components with lightweight materials like high-strength steel, magnesium (Mg) alloys, aluminum (Al) alloys, carbon fiber, and polymer composites has the potential to directly reduce the weight of a vehicle's body and chassis by up to 50 % (Gibbs et al., 2013) and in turn improve the range, handling, and safety of BEVs. To this end, BEV manufacturers, such as Tesla, have turned to giga-casting technology for building body-in-white architectures (Baser et al., 2022). This process involves a series of aluminum die-casting machines (giga press) to produce large aluminum castings that reduce assembly time, assembly line real state, and, most importantly, vehicle weight. These advances have led to a significant rise in the average aluminum content of BEVs from under 300 kg (643 net pounds per vehicle (PPV)) in 2020 to over 400 kg (885 PPV) in 2022. Furthermore, an additional 45 kg (100 PPV) is anticipated by 2030 (Ducker Holdings, 2023).

The increased aluminum content in BEVs has significant ramifications in the form of increased GHG emissions (GREET: The Greenhouse Gases, 2019; Wang et al., 2023), corresponding to an average of 3210 kgCO2e per vehicle (considering 643 PPV) stemming from aluminum production of 2020 BEV models. This number is expected to increase drastically by 2030 to 4920 kgCO2e per vehicle (considering 985 PPV), an outstanding 53 % (1710 kg) increase from 2020 models. This can result in aluminum production GHG emissions of upwards of 4180 kgCO2e over equivalent ICEVs, which on average contain 85 % less aluminum (Ducker Holdings, 2023).

Vehicle lightweighting is frequently viewed as an appealing remedy for the continuously increasing energy requirements in the transportation sector (Akhshik et al., 2017; Palazzo and Geyer, 2019), particularly when considering the substantial 29.5 *EJ* (exajoules) of energy consumed across all modes of transportation in the U.S. in 2016 (Lewis et al., 2019). Reducing vehicle weight by employing lightweight materials such as aluminum can reduce a BEV's electrical consumption and, in turn, improve its range, handling, and safety characteristics. Nevertheless, given that aluminum production emits significantly more greenhouse gases than steel production (GREET: The Greenhouse Gases, 2019; Wang et al., 2023; Lewis et al., 2019), it becomes imperative to conduct a comprehensive tradeoff analysis, covering various stages of the Life Cycle Assessment (LCA) tool, particularly focusing on production and utilization phases. This analysis is essential to ascertain the genuine effectiveness of the vehicle lightweighting process. As a hypothetical case study, we analyze the effect of reducing the vehicle weight of a 2017 Tesla Model 3 LR (TM3) on the car's electrical consumption. Specifically, we lightened the vehicle's BIW by 140 kg (H1-TM3), which corresponds to the predicted increased aluminum content (Ducker Holdings, 2023) as a partial substitution of conventional iron and steel components. We simulated utilization phase tests using the lightened model and the methods presented in §2.3. The H1-TM3 model achieved a 5 % reduction in electrical consumption on both the UDDS and HWFET driving profiles, respectively. The lower electrical consumption can lead to a potential reduction of upwards of 790 kgCO2e of the total vehicle GHG emissions, considering a utilization emission of 79.1 gCO2e/km and a vehicle life span of 200,000 km (refer to §3.2.2). We conducted an additional case study on a similar hypothetical vehicle, drastically reducing its total weight by 300 kg (H2-TM3) due to directly substituting its iron and steel components. This vehicle achieved an improvement of 10 % in its average electrical consumption, corresponding to a reduction in GHG emissions of 1580 kgCO2e. We note that the replacement of steel components with aluminum alloys resulted in additional production GHG emissions of 380 (+3 %) and 810 (+7 %) kgCO2 for H1-TM3 and H2-TM3, respectively. Furthermore, these additional GHG emissions offset by upwards of 50 % the emission reductions achieved during the utilization phase due to the lightweighting process. These results are summarized in Table 4.

Our case studies revealed that the lightweighting process with added aluminum could yield noticeable improvements in the overall BEV carbon footprint by reducing GHG emissions by upwards of 770 (−3 %) kgCO2e, considering the H2-TM3 model with a substantial 300 kg weight reduction. These moderate enhancements offer tangible proof of the advantages of the lightweighting procedure, contrasting with previous studies that reported inconclusive findings (Palazzo and Geyer, 2019). There are a few factors contributing to these results; first, we integrated new pathways for aluminum recycling, in which 80 % of cast aluminum in the automotive sector originates from recycled sources, in contrast to only 26 % for steel (Wang et al., 2023). Moreover, incorporating recycled materials reduces the kgCO2e per kilogram of cast aluminum from approximately 9.74 for virgin aluminum to 3.18 for the average aluminum (see Appendix A), including domestic (US) and imported materials. This shift notably alters the relative carbon footprint of aluminum versus steel in the chassis. Another crucial consideration for lightweighting studies is the proportion of global aluminum production. This value is a determinant of aluminum-related GHG emissions, which heavily rely on the electricity source and vary significantly based on the country of production. For instance, the environmental impact differs when aluminum is manufactured in China using coal compared to Europe and the US. Moreover, the specific value and proportion of

Table 4
Impact of lightweight materials on the GHGs of BEV.

LCA Phase	TM3	H1-TM3	H2-TM3
Lightweighting [kg]	–	−140	−300
Utilization test: UDDS [Wh/km]	160.1	151.1	140.6
Utilization test: HWFET [Wh/km]	174.9	167.0	157.9
Change in Utilization GHG [kgCO2e]	–	−790	−1580
Change in Production GHG [kgCO2e]	–	380	810
Net GHG of LW [kgCO2e]	–	−410	−770

imported aluminum fluctuate annually. Lastly, we emphasize that the enhanced carbon footprint highlighted in this study stems from energy savings during the utilization phase, accomplished through detailed dynamic modeling of the vehicles. As mentioned in §4.3, BEVs may have a shorter lifespan compared to ICEVs, which would reduce the overall improvements from lightweighting. For example, considering 160,000 km as the expected life of the BEVs (Kawamoto et al., 2019), the savings achieved through lightweighting would be reduced by around 40 %, resulting in a Net GHG of LW of −250 kgCO2e and −445 kgCO2e for H1-TM3 and H2-TM3, respectively.

5. Summary and conclusions

This study presents modeling the material and dynamic operation of two electric vehicles for an accurate life cycle assessment and, in turn, an estimate of their carbon footprint. The vehicle's production phase was modeled based on accurate teardown data of the vehicles from the individual parts and material compositions. The utilization phase was modeled accurately, including its components, such as the high-voltage battery, e-drive, tires, and aerodynamic forces. The controllers in the powertrain and wheels provided more reliable modeling of the vehicles' regenerative braking and energy efficiency. This phase's simulation data was validated with errors of less than 1 % from driving tests obtained from the EPA. These studies show that the potential to reduce emissions is far greater when considering the energy source than the charging type.

Accurate LCA analysis is crucial to coordinating efforts to reduce the carbon footprint of transportation systems by considering these technologies as part of encompassing model-based representations of energy systems and allowing for optimization and computational analyses (Kakodkar et al., 2022). We showed the effect of the assumptions in the LCA analyses of BEVs, such as their expected life and energy source. These assumptions can significantly change their carbon footprint and must be considered when electrification is encouraged. Specifically, our study suggests at least three main considerations in the design and utilization of electric vehicles to reduce their carbon footprint: i) use cleaner battery technologies such as LFP batteries instead of NMC and NCA materials, which can save up to 30 % of the battery production emissions, ii) a thorough analysis of lightweighting, especially when replacing steel with lightweight materials such as Aluminum; and iii) use station charging instead of home charging, which is associated with much lower charging efficiency. While these changes result in some lost efficiencies (lower energy density and increased mass), they are more effective and more immediate than other long-term solutions, such as changing the electricity source to renewables. We note some parameters that affect this study are: i) The LCA assessments and pathways can be different from one platform (GREET: The Greenhouse Gases) to another (Damyanov et al., 2021), ii) the GHG of aluminum is very dependent on the country of origin and the global values are much larger than the ones in the US and Europe (McMillan and Keoleian, 2009); and iii) the degradations of the BEV efficiency and increased consumptions with battery aging. This is due to the increase in ohmic resistance over time (Zou and Zhang, 2019), which causes the power loss of BEVs to increase. Therefore, the energy required per kilometer of driving increases for BEVs.

In addition, battery production is highly dependent on the country of origin. Our assumption for the battery was based on production in the USA. Aluminum plays a critical role in lightweighting, and to reduce costs, aluminum is usually imported from outside the US while having higher GHG production. This underscores the global nature of the supply chain and its impact on GHG emissions. We note that while 90 % of steel is recyclable, typically about 25 % recycled steel is used in the body-in-white fabrication, whereas aluminum components can be cast from over 80 % recycled aluminum. Therefore, focusing on the lightweighting of the cast components yields additional carbon footprint savings. Future work includes further analyzing the sensitivity of parameters, losses in regenerative braking due to the limits on the state of charge, the effect of lightweight material on the production, recycling, and utilization phase, and including more comparative studies with others and conventional vehicles.

CRediT authorship contribution statement

Omidreza Ahmadzadeh: Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. **Renato Rodriguez:** Investigation, Methodology, Software, Visualization, Writing – original draft. **Jonah Getz:** Methodology, Software, Data curation. **Samy Panneerselvam:** Conceptualization, Resources, Writing – review & editing. **Damoon Soudbakhsh:** Conceptualization, Funding acquisition, Project administration, Methodology, Software, Validation, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We do not have the permission to share the teardown data of the vehicles, but we will be able to share other data such as overall LCA analysis, and the dynamics modeling upon request.e vehicles

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N/A.

Appendix A. Raw material emission

Here, we provide a table of the production GHG for the main materials used in BEVs (Wang et al., 2023).

Table A.1
GHG emissions per kilogram of material.

Material	GHG [kgCO2e/kg]
Carbon Fiber	12.18
Cast Aluminum, average	3.18
Cast Aluminum, recycled	1.54
Cast Aluminum, virgin	9.74
Coolant	0.60
Copper	4.03
Glass	1.72
Iron	0.92

(*continued on next page*)

Table A.1 (*continued*)

Material	GHG [kgCO2e/kg]
LFP (Active Material)	4.44
NCA (Active Material)	27.08
NMC811 (Active Material)	25.67
Plastic	3.54
Polyethylene	2.36
Rubber	3.86
Sheet Aluminum, average	7.87
Sheet Aluminum, recycled	2.47
Stainless Steel	0.86
Steel, average	2.42
Steel, virgin	3.03

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