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Life-cycle assessment for battery trucks by integrating battery recycling

Master Thesis

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By
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Abstract

Trucks today are responsible for 65% of all freight-related CO_2 emissions and will probably remain the main form of road transport for the coming decades. To make a real shift toward sustainable freight transport, a Life Cycle Assessment (LCA) of battery electric trucks (BETs) compared to internal combustion engine trucks (ICETs) has been conducted, with a focus on the European context considering a reference scenario, in which, the environmental impact will be study with current technologies and a dynamic scenario, in which, the environmental impact will be assess considering future improvement in electricity mixes, material manufacturing and recycling technologies. Results show that although BETs have higher production emissions, mainly due to battery manufacturing, they achieve a 47% reduction in total CO_2 emissions compared to ICETs in the reference scenario for 2025, driven by significantly lower emissions in the use phase.

Additionally, the analysis highlights the environmental benefit of battery recycling, with hydrometallurgical processes showing better performance than pyrometallurgical alternatives due to lithium recovery and lower energy use. A Monte Carlo simulation was conducted to account for variations in electricity mixes across European countries, revealing a strong dependency of battery electric truck (BET) performance on the carbon intensity of local grids. A prospective LCA further explores different future scenarios (SSP1 and SSP2), showing up to 75% emissions reduction in BETs produced in 2040 under sustainability driven conditions.

These findings emphasize the importance of decarbonizing electricity generation, improving not only recycling technologies, but also production technologies, and considering regional energy contexts in the transition to sustainable freight transport.

Acknowledgements

First of all, I would like to thank Comillas Pontifical University (ICAI) and the Technical University of Denmark (DTU) for the opportunity to complete the double degree program (T.I.M.E.) at both institutions. I would also like to thank my friends, both in Madrid and Copenhagen, and most of all, my family for their constant support throughout these years.

Contents

1 Introduction

In recent years, the field of mobility has developed a transition toward more sustainable solutions to mitigate climate change. This transition will not only affect the mobility of people but also the transportation of goods, the logistics sector. In the next years, battery trucks will be integrated into the logistic industry and will likely replace diesel trucks entirely. This transition could happen because electric trucks are cheaper to operate in the long run. Another potential benefit is their reduced CO_2 footprint. In this case, the real carbon footprint will be evaluated using the Life Cycle Assessment (LCA) method. However, obtaining accurate results is challenging due to the development of various technologies, which can impact the sector's carbon footprint.

According to the study [2], most of the LCA literature on electromobility are focused on passenger cars. Nevertheless, freight transport accounts for a significant portion of greenhouse gas (GHG) emissions within the mobility sector. For instance, in Germany, transport is responsible for approximately 20% of the country's total annual GHG emissions (around 0.8 Gt CO_2eq), with heavy-duty vehicles alone contributing between 7% and 8%. According to a study from the International Council on Clean Transportation [3], the life-cycle emissions on electric cars over the lifetime is between 66% and 69% lower compared to gasoline cars in Europe, and it will be 81% lower if the electricity supply is powered by renewable energy. In addition, recycling the used batteries contribute to a reduction of 8.3% in the electric cars climate impact and future electricity mix improvements provides a 9.1% reduction in GHG emissions [4].

These findings from electric cars highlight the environmental benefits of electrification in transportation. Based on this, it is reasonable to expect similar potential emissions reduction in the freight sector. Therefore, this study will conduct a LCA study of battery electric truck (BET) considering different scenarios, including battery recycling and future improvements in electricity mix and different technologies.

1.1 Literature review

1.1.1 Battery Electric Trucks for Sustainable Freight

Trucks have always played a fundamental role in the transportation sector, serving as the main mode of road transport. Trucks today are responsible for 65% of all freight-related CO_2 emissions and will likely stay the main form of road transport for the coming decades. Right now, there are no carbon-neutral solutions for long-haul heavy-duty trucks that are ready for widespread use. To make a real shift toward sustainable freight transport, further progress is needed in vehicle technology as well as in building the necessary supply and charging infrastructure [5].

Freight transport is responsible for over 40% of all transport-related CO_2 emissions, yet policy efforts have mostly focused on passenger vehicles. Even with strong policies, freight demand is expected to more than double in the next thirty years. To seriously cut emissions and move towards sustainable freight, bold and fast action is needed now [5].

One recent study from Scania [6], highlights the significant environmental benefits of battery electric trucks (BETs). According to their LCA, they can achieve a reduction of up to 68% in CO_2 emissions compared to internal combustion engine trucks (ICETs), run by diesel, over the entire life cycle. This reduction considers not only the use phase, where BETs produce zero tailpipe emissions, but also improvements in energy efficiency and the increasing share of renewable energy in electricity production. These findings demonstrate the strong potential of BETs to contribute meaningfully to the decarbonization of freight transport.

BETs have historically faced major challenges for long-haul applications due to high energy demands and the low energy density of batteries. However, recent advances in battery technology are making electric heavy-duty trucks increasingly viable, both technically and commercially. As battery prices are projected to continue declining, the life cycle costs of electric trucks are expected to become competitive with, or even lower than, those of diesel trucks. Several manufacturers have already introduced battery electric truck models with ranges exceeding 300 km, meeting the minimum operational requirements for regional transport under EU regulations [7]. These developments suggest that the transition towards battery electric freight transport is becoming not only feasible but also economically attractive.

1.1.2 Battery Recycling and End of Life Strategies

The end-of-life or recycling phase plays a fundamental role in the environmental impact of the product. In the case of BETs, battery recycling could boost the transition to this technology, reducing costs and waste. Li-ion batteries have seen increasing interest in their recovery for second life applications. There are 3 points in which recycled batteries can have a key role:

1. Reuse: using the battery to its full potential in the initial product. Reuse is the first option in circular economy. A good example of battery reuse is the mid-life renovation on several hybrid electric city buses, in which Scania, instead of mounting brand-new batteries that would outlast the buses, they installed reused batteries whose lifetime would match the remaining lifespan of the buses [8].

2. Repurpose: a second life for the batteries in other products. This is especially relevant for Li-ion batteries in hybrid and electric vehicles (HEV/EV), as they are deemed unsuitable for vehicle use once their capacity falls to 80% of its original capacity. These second-life batteries are seeing much interest in being used as grid-level storage devices [9], such as Battery Energy Storage Systems (BESS)

3. Recycle: reducing the need for virgin materials in new batteries. The recovery rate of batteries for electric vehicles can reach up to 95% of the materials [10]. The main components of electric vehicles batteries that can be recycled are lithium, cobalt, nickel and copper.The main battery recycling techniques are: Hydrometallurgical and Pyrometallurgical process.

As part of the shift toward a low-carbon future in response to climate change, electrification plays a crucial role. Following a study from the International Energy Agency [11], the demand of critical minerals, such as, cobalt, nickel, lithium and copper will increase in the following year, unlocking the potential for significant contributions from secondary supply. Primary copper demand will increase by 3% annually while the demand of nickel and cobalt will increase by 6.5% due to the production of lithium-ion batteries. The highest increase in demand is for lithium, 18% annually until 2030. Recycling these critical mineral provides a reduction of 40% in primary supply for copper and cobalt and 25% reduction for lithium and nickel in 2050. Although the primary supply is expected to increase in the following years, it is important to highlight the benefits of recycling to reduce this supply and environmental footprint[11].

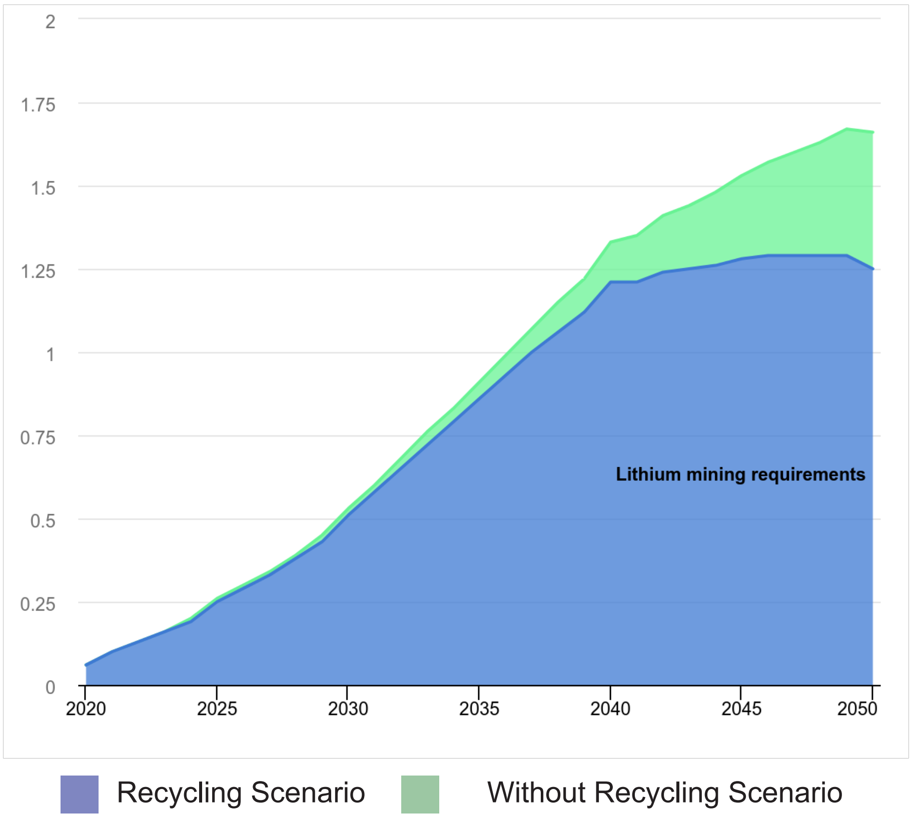


Figure 1.1: Lithium: mining requirements in the Announced Pledges Scenario, 2020-2050 [11]

Pyrometallurgical Process

Pyrometallurgical recovery technology refers to the fission and conversion of cathode materials at high temperatures, allowing valuable metals to be recovered in the form of oxides or alloys [12].

The two-furnace pyrometallurgical process is the earliest and most established method for recycling lithium-ion batteries (LIBs). It begins by pyrolyzing the batteries in the first furnace to remove the plastic casing and evaporate the electrolyte. After this initial stage, the material is cooled and transferred to a second furnace for the final melting process [13]. As an output, valuable iron (Fe), cobalt (Co), nickel (Ni), and manganese (Mn) metals are converted to alloys. However, lithium is lost as slag or dust during this process [14]. However, this method has notable disadvantages: it requires a high initial investment and operational costs, and consumes large amounts of energy due to the need for two separate furnaces. Additionally, the quality of the recovered materials is generally lower compared to other recycling alternatives [13]. This study [13], also mentions that the final alloy can later be recycled separately through a hydrometallurgical process, which is why it is included in Figure 1.2.

Hydrometallurgical Process

Hydrometallurgical methods mainly use water-based solutions to extract and separate metals from lithium-ion batteries (LIBs) [15]. After removing the aluminum and copper current collectors, the battery materials are typically treated with sulfuric acid (H_2SO_4) and hydrogen peroxide (H_2O_2), although other acids such as hydrochloric acid (HCl), nitric acid (HNO_3), and organic acids like citric and oxalic acid are also commonly used. Once the metals are dissolved into solution, they can be selectively recovered by adjust-

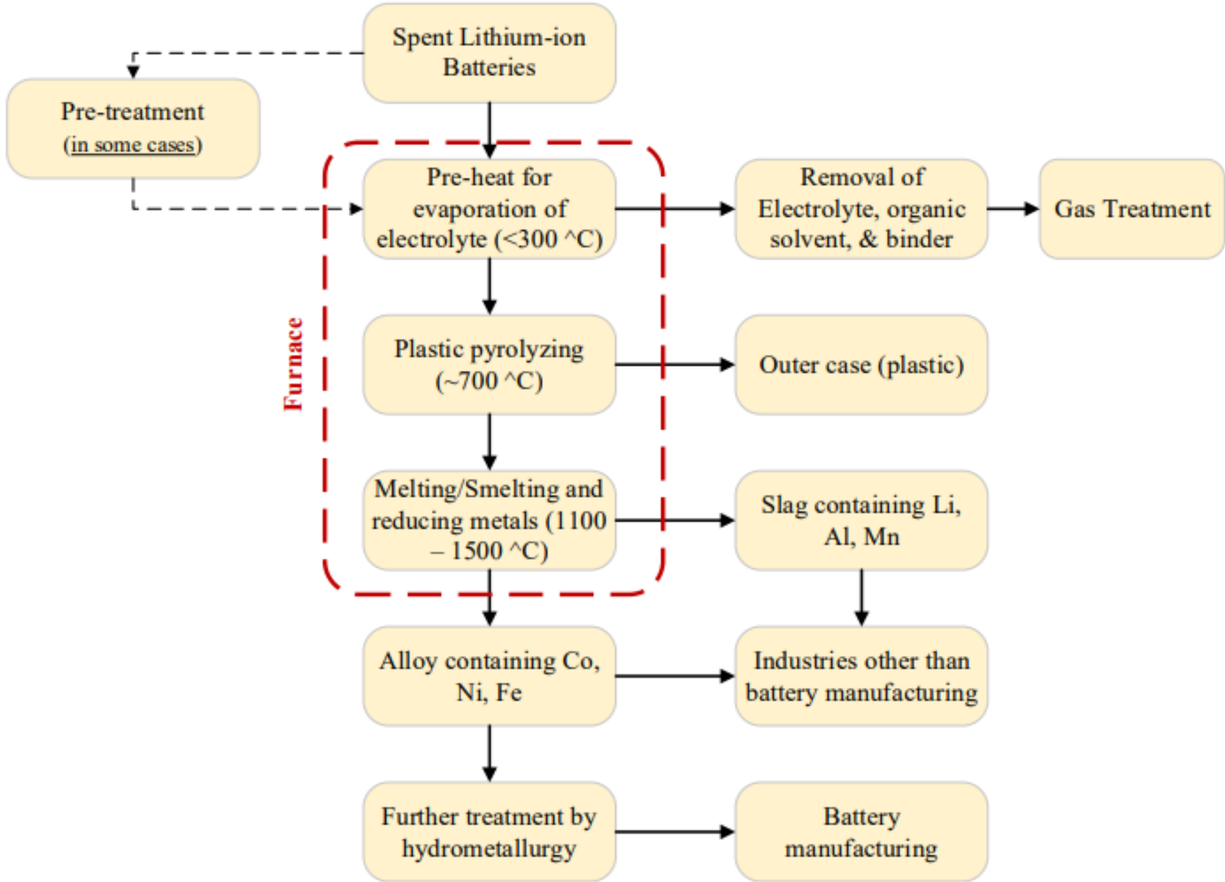


Figure 1.2: The outline of the pyrometallurgy recycling method [13]

ing the pH or using organic solvents containing extractants such as dialkyl phosphates or phosphinates [15]. Hydrometallurgy is considered a mature and reliable recycling method, especially in countries like China [13]. In these processes, spent LIBs are treated similarly to ores, but unlike pyrometallurgical methods, the objective is to recover as much material as possible, supporting a circular economy approach [2]. Typically, hydrometallurgy consists of three main stages: pretreatment to remove impurities, leaching to dissolve metals, and purification and recovery of materials. Pretreatment is critical, as the chemical recovery processes are often designed for specific materials [13]. In practice, pretreatment involves dismantling the battery packs, discharging and separating the modules into cells, shredding them, and then segregating components such as electrolytes, electrodes, and metallic scraps like aluminum, iron, and copper. The cathode materials are then processed for leaching, while graphite may either be separated earlier or recovered as a by-product [13].

It is important to note that the input of the hydrometallurgical process could also come from a pyrometallurgical recycling plant [13]. In recent years, hydrometallurgy has attracted increasing attention for several reasons. First, it enables the recovery of a wide range of materials from lithium-ion batteries (LIBs), including lithium, cobalt, manganese, nickel, copper, aluminum, and graphite . Many of these valuable materials are lost during pyrometallurgical recycling, making them unavailable for reuse in new batteries. Second, hydrometallurgy generally consumes less energy than pyrometallurgy. Additionally, hydrometallurgical methods tend to produce higher-quality recovered materials, making them a reliable and efficient option for recycling LIB components.[13]

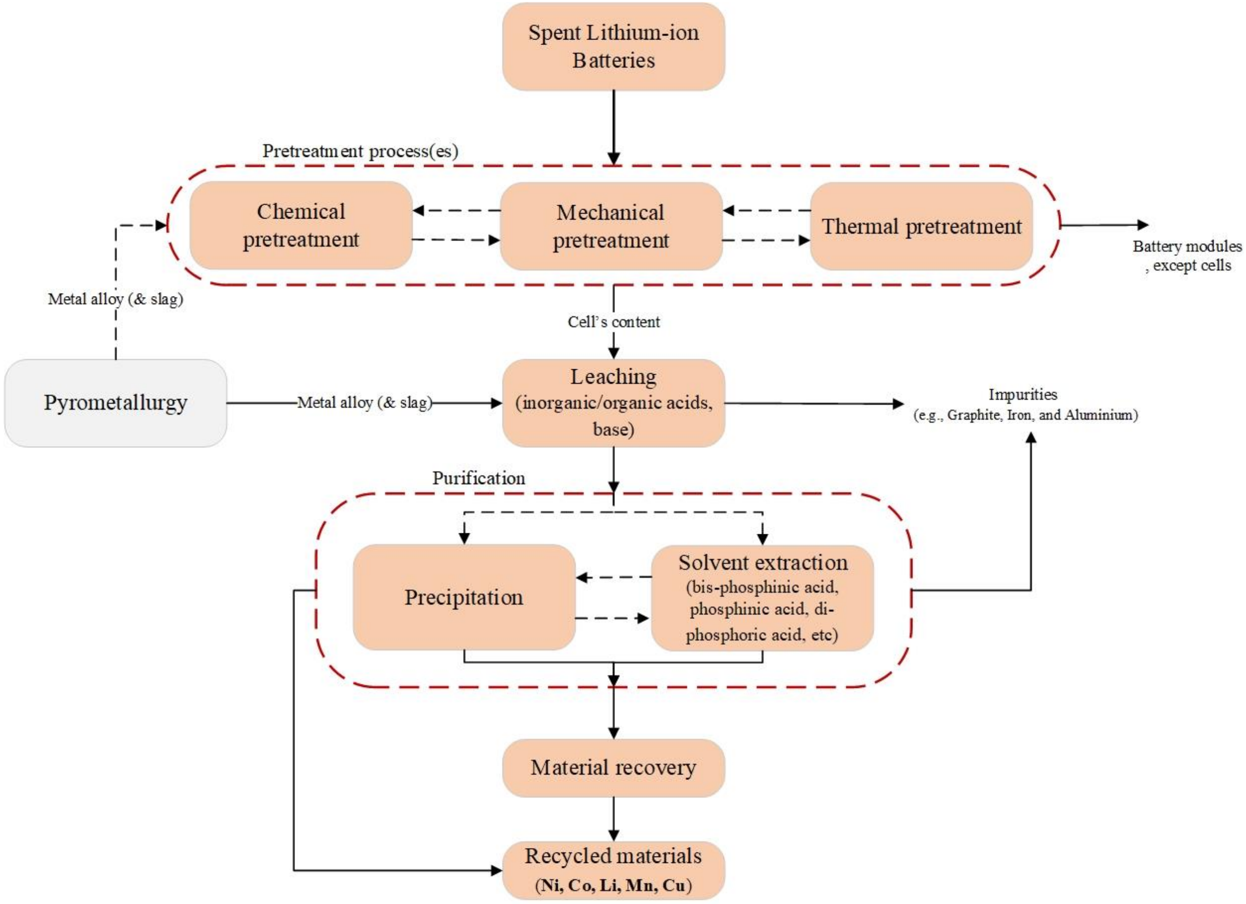


Figure 1.3: The outline of the hydrometallurgical recycling method [13]

1.2 Research motivation and Contribution of the Paper

Although the environmental performance of electric vehicles and battery recycling processes have been widely studied, they are often assessed separately, demonstrating a gap in the scientific literature. In particular, the combined effects of future improvements in electricity mixes, advances in material manufacturing processes, and the integration of battery recycling into the LCA of BETs have not yet been fully investigated. These elements are crucial to understanding the true potential of BETs in contributing to the decarbonization of freight transport. This study presents a comprehensive LCA that integrates these aspects to assess the environmental performance of present and future BETs. The following research questions are investigated:

1. What are the environmental impacts of a BET operating under current technologies and energy conditions?
2. How might these impacts change when future improvements, such as increased renewable energy shares and advancements in material production, are considered?
3. To what extent can battery recycling reduce the net environmental impacts across the life cycle of BETs?

2 Methodology

LCA is a structured, comprehensive and internationally recognized method for evaluating environmental impacts. It measures all relevant emissions, resource use, and the associated effects on human health, ecosystems, and resource depletion linked to goods and services. LCA considers the entire life cycle of a product, from raw material extraction, manufacturing, and use, to recycling and final waste disposal [16]. Typically, LCA is used as a comparative tool rather than for absolute assessments, and in this case, it will be used to compare diesel and electric trucks. LCA consists in four phases: goal and scope definition, inventory analysis, impact assessment, interpretation and discussion of results [16].

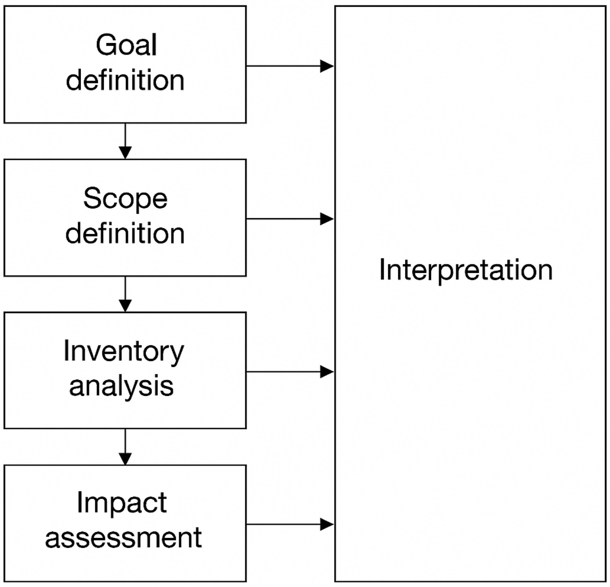


Figure 2.1: Framework of LCA methodology [17]

2.1 LCA Mathematical model

LCA is based on a structured mathematical framework that models the interactions between production processes, environmental emissions, and impact assessment methods. This framework can be expressed using the following formula [18]:

$$h = QBA^{-1}f \tag{2.1}$$

Each item has the following characteristics:

- A: the technological matrix, is a mxm size matrix, which represents the technological relationship among processes.
- B: the intervention matrix, is a pxm matrix, which describes the resource consumption and emissions generated by each production process represented in the technology matrix (A).

- Q: the characterization matrix, is a lxp matrix size, which contains the characterization vectors of different impact categories (global warming, land use...).
- f: the final demand vector of size m, based on the functional unit.
- h: the output of the LCA model.

This mathematical formulation provides a clear and consistent way to quantify the environmental impacts associated with complex production system. With this break down, is easier to understand how inputs, emissions and impacts interact.

2.1.1 Numerical example explanation

This section presents a process flow representation based on a real-world example. It illustrates the inputs and outputs involved in generating 1000 kWh of electricity from fuel-based energy sources. To represent quantified flows in unit processes, the concept of a linear space is introduced. A linear space allows multidimensional data (such as different flows) to be uniquely expressed as a vector, where each coordinate corresponds to a specific flow with a defined value. This mathematical structure provides a clear and consistent way to model complex systems in LCA [19].

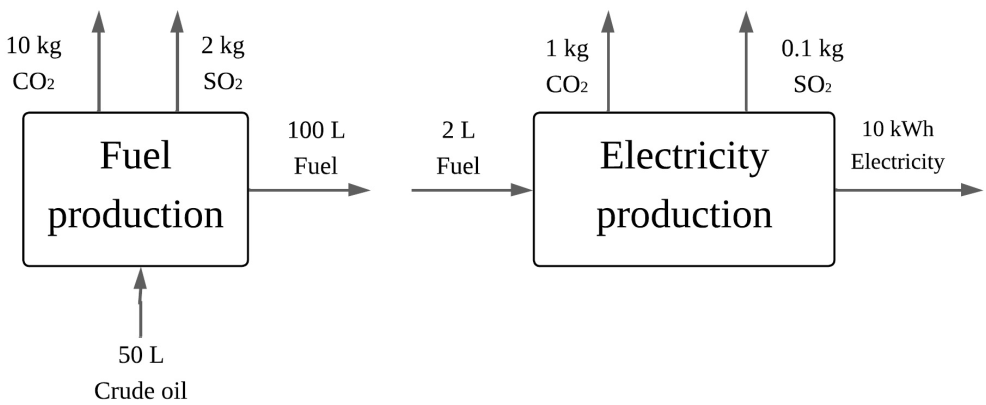


Figure 2.2: Diagram flow example

Considering that to obtain 10 kWh of electricity, 2 litres of fuel are needed. This process emits 1 kg of CO_2 and 0.1 kg of SO_2. This process can be represented as a vector with the following nomenclature.

$$\begin{pmatrix} \text{litre of fuel} \\ \text{kWh of electricity} \\ \text{kg of carbon dioxide} \\ \text{kg of sulphur dioxide} \end{pmatrix}$$

For this process, the following vector is obtained. The 2 litres of fuel are considered an input, which is why the value is negative. The minus sign indicates the direction of the flow. In contrast, electricity, carbon dioxide, and sulphur dioxide are outputs and therefore their values are positive.

$$\mathbf{p} = \begin{pmatrix} -2 \\ 10 \\ 1 \\ 0.1 \end{pmatrix}$$

Now, let us consider a second unit process for producing fuel. For producing 100 litres of fuel, 50 liters of crude oil are needed and 10 kg of CO_2 and 2 kg of SO_2 are emitted to the environment. In the previous vector, there is not a dimension for crude oil. A fifth dimension needs to be added to the vector of this process.

$$\begin{pmatrix} \text{litre of fuel} \\ \text{kWh of electricity} \\ \text{kg of carbon dioxide} \\ \text{kg of sulphur dioxide} \\ \text{litre of crude oil} \end{pmatrix}$$

For each process, the following two vectors are obtained, based on five dimensions.

$$p_1 = \begin{pmatrix} -2 \\ 10 \\ 1 \\ 0.1 \\ 0 \end{pmatrix} \quad p_2 = \begin{pmatrix} 100 \\ 0 \\ 10 \\ 2 \\ -50 \end{pmatrix}$$

Merging these two vectors we can obtain the A and B matrix, which are the technological matrix and intervention matrix, respectively.

$$\mathbf{P} = \begin{pmatrix} \mathbf{A} \\ \mathbf{B} \end{pmatrix} = \left(\begin{array}{rr} -2 & 100 \\ 10 & 0 \\ \hline 1 & 10 \\ 0.1 & 2 \\ 0 & -50 \end{array}\right)$$

Assuming that the environmental impact of 1000 kWh is to be calculated, the demand vector f is defined.

$$f = \begin{pmatrix} 0 \\ 1000 \end{pmatrix}$$

To get the inventory flow of the process the following calculation needs to be done:

$$g = BA^{-1}f$$

In this case for obtaining 1000 kWh of electricity, g_1 is 120 kg of CO_2, g_2 is 14 kg of SO_2 and g_3 is -100 litres of crude oil.

Once the inventory flow is calculated, the different environmental impact categories have to be calculated. This is where the Q matrix takes place. The Q matrix will reflect how these inventory flows will affect the environmental impacts categories selected. Assuming that the Global Warming Potential (CO_2-equivalent) and Acidification Potential (SO_2-equivalent) are chosen, the Q matrix will reflect how, in this case, CO_2, SO_2 and crude oil will affect each impact category.

Assuming that in the global warming potential category, 1 kg of CO_2 corresponds to 1 kg of CO_2-equivalent and 1 litre of crude oil corresponds to 0.5 kg of CO_2 -equivalent. For the acidification potential category, 1 kg of SO_2 corresponds to 1 kg of SO_2-equivalent and 1 litre of crude oil corresponds to 0.01 kg of SO_2-equivalent. The following Q matrix is obtained.

$$Q = \begin{bmatrix} 1.0 & 0 & 0.5 \\ 0 & 1.0 & 0.01 \end{bmatrix}$$

To obtain the impact vector h, the following calculation must be performed:

$$g = BA^{-1}f$$

As a result, generating 1000 kWh electricity will have an impact of 170 kg CO_2 equivalent and 15 kg of SO_2 equivalent.

2.2 Goal and Scope definition

The goal and scope definition phase involves establishing the objectives of the LCA study and setting the appropriate system boundaries [16].

The objective of this LCA is to evaluate the environmental impacts of a battery electric long-haul truck and a conventional diesel driven truck [6], with two main scenarios. A current scenario, in which, the enviromental impact will be study with current technologies and a dynamic scenario, in which, the environmental impact will be assess considering future improvements in electricity mixes, materials manufacturing and recycling technologies.

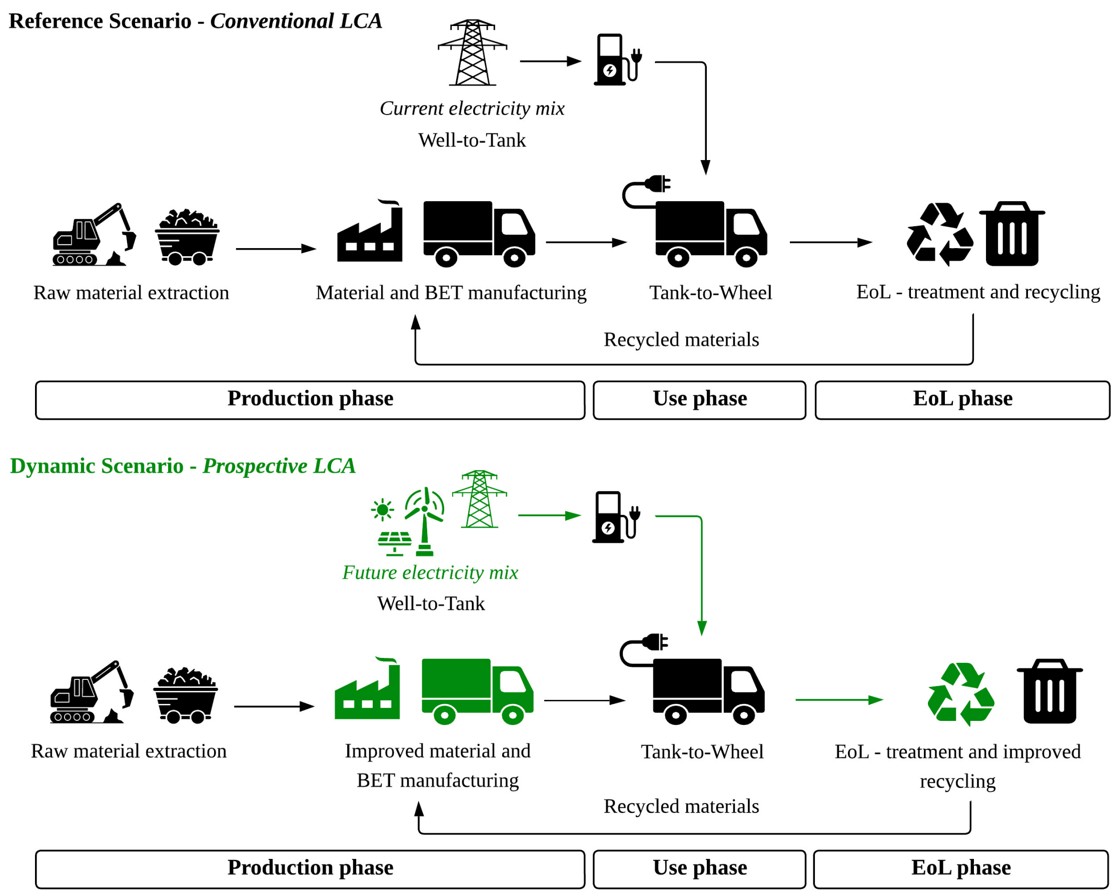


Figure 2.3: Reference and dynamic scenario diagram for BET [4]

2.2.1 Functional Unit

The functional unit (FU) of this study is defined as a long-haul truck operating over a distance of 1,000 kilometers under representative payload conditions, for both diesel and electric configurations. Since the primary function of long-haul trucks is to transport goods between locations, the functional unit is based on distance driven rather than other measures such as operating time.

Both vehicle configurations are as similar as possible, to ensure a fair and relevant comparison. The long-haul trucks modeled in this study are based on Scania vehicle specifications[6]. The following table provides an overview of the specifications for this type of truck.

The BEV Truck is powered by a motor of 400 kW and has a 624 kWh battery pack, while the ICE Truck is powered by a 460 hp diesel engine with Euro 6 emissions standards.

Table 2.1: Overview specifications of the vehicles [6].

Specifications	BET	ICET
Chassis adaptation	Articulated (tractor)	Articulated (tractor)
Wheel configuration	4x2	4x2
Chassis height	Normal	Normal
Axle distance (mm)	4 150	3 750
Suspension system, front / rear	Leaf / Air (type B)	Leaf / Air (type B)
Axle, front / rear	AM640S / AD400SA	AM420S / AD410SA
GVW technical (tonnes)	20.5	19
Propulsion	Electric motor EM C1-4, 400 kW (520 hp)	Diesel engine DC13 175, 460 hp
Battery capacity	624 kWh installed capacity	–
Gearbox	–	G25CM1 with retarder
Cab type	CR high	CR high
Cab length	20	20
Curb weight (tonnes)	10.2	8.0

2.2.2 System boundary

The study covers the entire life cycle of the vehicles, following a cradle-to-grave approach. It accounts for all stages, from raw material extraction and vehicle manufacturing to the operational phase and final disposal at the end of life [6].

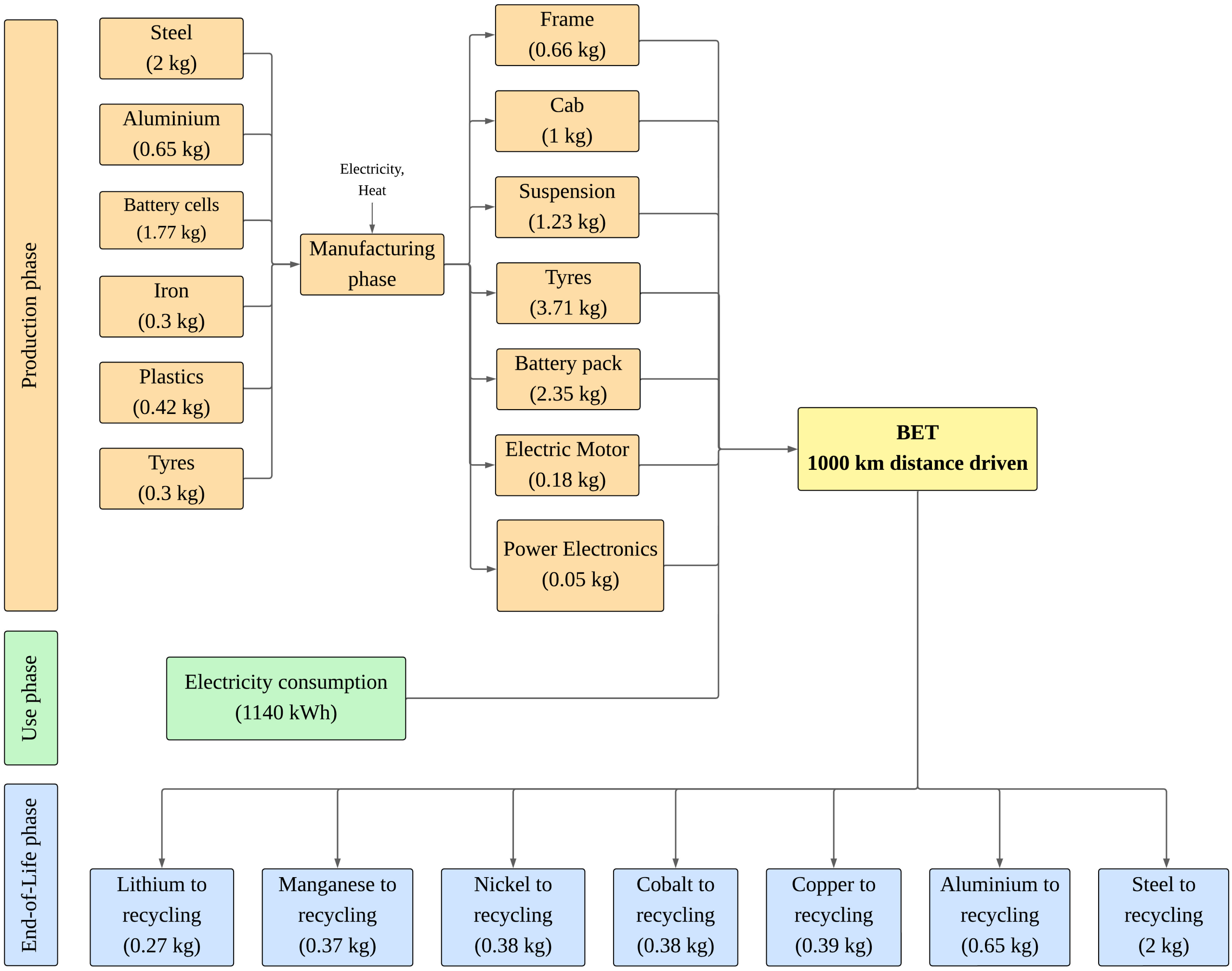


Figure 2.4: Illustration of functional unit reference flows of modeled system. Yellow:functional unit. Orange:production phase. Green: use phase. Blue:end-of-life phase

2.3 Inventory Analysis

Life cycle inventory (LCI) creation represents the second phase of an LCA study.It involves gathering and organizing data on elementary flows from all processes within the product system [16]. The analysis considers all processes identified as part of the product system, and the flows are scaled in accordance with the reference flow of product that is determined from the functional. In this case, it has been divided in three section: production phase, use phase and end-of-life phase.

2.3.1 Production phase

The production phase or cradle-to-gate includes raw material extraction, material processing, product manufacturing and logistics [6]. It covers only the stages from raw material extraction to the factory gate where the product is manufactured, before it is delivered to the consumer [20].

In this section, as shown in Table 2.2, the BET has been divided in seven components: frame, cab, suspension, tyres, battery pack, electric motor and power electronics. The frame, cab, and suspension have been assumed to be the same as a ICET [21].

The 624 kWh battery pack modeling is based on the study [22], and production takes place in China. Consequently, the emissions associated with battery manufacturing are calculated using the Chinese electricity grid mix. The battery cell for the battery pack is NMC 111 (Nickel Manganese Cobalt oxide) type. The transportation emissions have not been considered because the study only covers regional deliveries in China. While the battery production is modeled using the Chinese electricity grid mix, the rest of the truck components are assessed using the average European Union grid mix [23].

For the tyres [24], the quantity is extracted from the Bill of the Materials of the Scania study [6]. Unlike other truck components, the tyres have a different life cycle period, 105.000 kilometers, which affects the FU. It is known that electric vehicles are usually heavier than internal combustion engine vehicles, due to the battery pack, mainly. This additional weight increases the load on the tyres, leading to a reduced lifespan. Based on a study [25], the tyre wear in electric vehicles is between 20% and 30% higher because there are 24% heavier. In addition, on average, the first tyre replacement is 17.985 miles for electric vehicles compared to 24.355 miles for petrol and diesel cars, a 26% reduction in lifespan [26]. Although there are no recent studies based on truck tyres, based on the previous information, a 30% reduction of lifecycle period for the BET tyres has been assumed for the same tyre composition for both trucks. This assumption, based on tyre wear, aligns with the approach taken in the Scania study. [6].

For the electric motor of 400 kW has been assumed to be equivalent to four units of a 100 kW motor [4], proportionally scaled. Power electronics has been assumed to be the same as a passenger car [4].

Table 2.2: Material, energy, and electricity use per BET component and per (FU)

Truck Part	Qty (kg)	Qty/FU (kg)	Energy (MJ)	Energy/FU (MJ)	Electricity (kWh)	Electricity/FU (kWh)
Frame	854	0.66	–	–	–	–
Cab	1299	1.00	2058	1.58	852	0.66
Suspension	1600	1.23	–	–	604	0.46
Tyres	390	3.71	–	–	397	3.79
Battery Pack	3056.9	2.35	79200.66	60.92	23804.55	18.31
Electric Motor	232	0.18	59	0.45	75	0.58
Power Electronics	59	0.05	–	–	60	0.05

On the other hand, the ICET has been divided in five sections: frame, cab, suspension, tyres and engine. The frame, cab, suspension and engine are from the same source [21]. In the case of the tyres [24], the quantity and the tyre composition is the same as the BEV truck but the lifeycle period is higher, 150.000 km [27].

Table 2.3: Material, energy, and electricity use per ICET component and per functional unit (FU)

Truck Part	Qty (kg)	Qty/FU (kg)	Energy (MJ)	Energy/FU (MJ)	Electricity (kWh)	Electricity/FU (kWh)
Frame	854	0.66	–	–	–	–
Cab	1299	1.00	2058	1.58	852	0.66
Suspension	1600	1.23	–	–	604	0.46
Tyres	390	2.60	–	–	397	2.65
Engine	1176	0.90	–	–	811	0.62

Table 2.4: Material composition (in tonnes and %) for BET and ICET

Material	BEV		ICE	
	Tonnes	%	Tonnes	%
Battery cells	2.31	31%	–	
Steel	2.59	35%	2.85	53%
Aluminium	0.77	10%	0.32	6%
Plastics & Rubber	0.54	7%	0.63	12%
Iron	0.40	5%	0.91	17%
Other metals	0.08	1%	0.04	1%
Electronics	0.18	2%	–	
Tyres	0.39	5%	0.39	7%
Rest	0.16	2%	0.20	4%
Sum	**7.40**		**5.32**	

2.3.2 Use phase

The use phase accounts for a significant share of the total life cycle environmental impact of the trucks [6]. This phase is divided in well-to-tank and tank-to-wheel. Maintenance activities have not been considered in this study, only tyres replacement during the use phase as part of the overall life cycle.

Energy and fuel consumption

Energy and fuel consumption data are based on the Scania report [6]. For the BET the energy consumption is 1.14 kWh/km and for the ICET is 23.56 l/100 km of diesel. These data were obtained using the VECTO simulation tool, used in the Scania study [6], which applies different payload for both long haulage and delivery cycles to ensure accurate results. The payload varies between 2.6 and 19.3 tonnes.

Energy losses usually occurs during BET charging. These losses depend on battery temperature, charging speed or battery charging state [6]. Following the Scania report [6], a factor of 10% loss is included in the energy consumption of the BET.

Well-to-Tank

The well-to-tank section considers the environmental impact of electricity generation and diesel production.

The electricity generation is based on the european grid mix from Ember and Energy Institute [28], with a carbon footprint of 281 gCO_2/kWh. In this case, as the FU is 1000 km driven distance, the electricity consumption will be 1140 kWh.

The fuel consumption only considers diesel production, ignoring diesel transport emissions. The data is based on a European Commission document [29]. In this case, the diesel consumption will be 2356 liters.

Tank-to-wheel

This section only applies to the ICETs because BETs do not produce exhaust emissions during the use phase. Emissions data are based on the EMEP/EEA air pollutant emission inventory guidebook 2023 [30], which provides exhaust emissions data for articulated diesel trucks (14-20 tonnes) with Euro 6 emissions standards. The following emissions are considered: CO, CH_4, NO_2, N_2O, NH_3, Pb, CO_2.

Non-exhaust emissions have not been considered for this study. Non-exhaust emissions are emissions that are not produced by the combustion of fuel in the engine [6]. They are usually emissions of particulates matter due to road vehicle tyre and break wear and road surface wear [30]. For future studies it will make sense to consider them, as electric vehicles are heavier than combustion vehicles, in passenger cars there is an increment of 7-10% of tyre wear emissions for electric vehicles [30].

Table 2.5: ICET Exhaust Emissions

Vehicle	CO (g/km)	CH_4 (g/km)	NO_2 (g/km)	N_2O (g/km)	NH_3 (g/km)	Pb (g/km)	CO_2 (g/km)
Euro VI A/B/C	0.108	0.019	0.287	0.035	0.009	1.73E-04	531.595

2.3.3 End of Life

Battery Electric Truck

In the end-of-life phase, recycling plays a key role. All data on recyclable materials and recycling rates are taken from the same study [31], based on China. Transportation emissions has not been included because the study [31] only consider battery packs from China, not from Europe. Although the original study [31] focuses on a LCA of NMC 333 battery pack, an adaptation has been made in this report for the NMC 111 battery cells. The main adaptation is that the cathode of the NMC 111 use lithium carbonate instead of lithium hydroxide.The recovery rate for the lithium carbonate has been assumed to be the same as for lithium hydroxide. For this phase, both hydrometallurgical and pyrometallurgical battery recycling processes are considered. In addition, steel, aluminium, and copper are included in recycled materials [31]. In this phase, the benefits of potential recycled materials have been evaluated, following an avoided burden approach [32].

For aluminium recycling, the melting and casting technique has been implemented, achieving a recovery rate of 95.5% [31]. This recovery rate will be different for the aluminium in the battery cells. For steel recycling, the electric arc furnace process has been applied, which is the main recycling technique which involves remelting scrap steel to produce new steel[33].In this case the recovery rate is 86.8% [31]. Copper scrap is treated by electrolytic refining, with a recovery rate of 76.3% [31]. This recovery rate will be different for the copper in battery cells.

For the battery cells, Al and Cu have a recovery rate of 93.8%. In the hydrometallurgical process, Li^{I}, Co^{II}, Ni^{II} and Mn^{II} (all as sulfates) from the battery electrodes have a recovery rate of 93.6%. In the pyrometallurgical process, Co^{II}, Ni^{II} and Mn^{II} have a recovery rate of 93.6% but Li^{I} is not recovered [31].

A total of 54.5% of the battery cells' mass is recyclable, in which, 51.5% is recovered. For the battery pack, 62% of it is recyclable, which, 58% is fully recovered. For the rest of the truck, 67% of the mass is recyclable, recovering the 59%, only considering that steel, aluminium and copper are recyclable materials.

Internal Combustion Engine Truck

In this case, the only materials available for recycling are steel, aluminium and copper. The recycling techniques will the same as for the BET. The recovery rate for the steel is 86.8%, for the aluminium 95.5% and for the copper 76.3%. The ICET is 61% recyclable, in which, 88% is recovered.

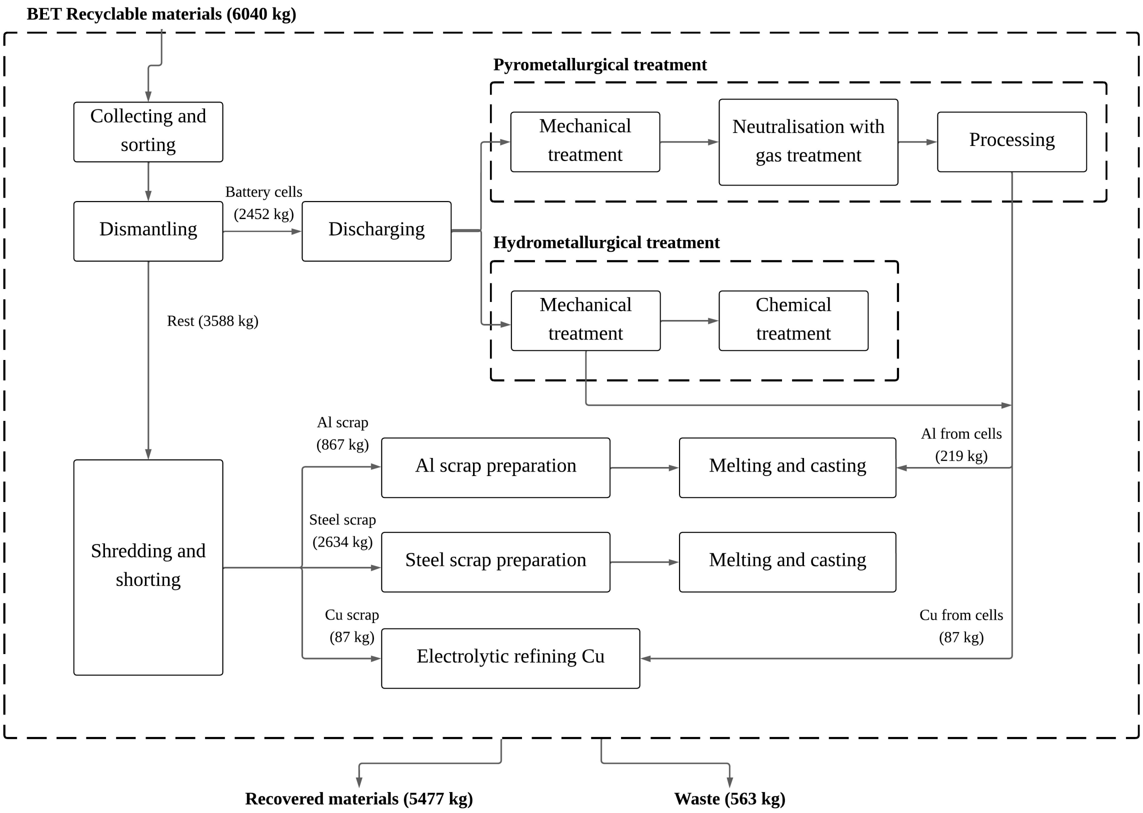


Figure 2.5: Recycling process diagram. During dismantling, the battery cells are separated from the rest of the components, discharged, and then recycled through a hydrometallurgical process. The copper from the battery cells is directly recycled via electrolytic refining, while the aluminium from the battery cells is recycled through a melting and casting process.Non-battery components (such as aluminium, steel, and copper) are shredded and sorted. Aluminium and steel are then prepared and recycled through melting and casting, whereas copper is sent directly to electrolytic refining

Table 2.7: Amounts and recovery rates of recovered materials from the ICET

Recovered material		**ICET recycling**
Al	Recyclable [kg]	323.29
	Recovery rate	95.5%
Cu	Recyclable [kg]	41.69
	Recovery rate	76.3%
Steel	Recyclable [kg]	2861.18
	Recovery rate	86.8%
Recyclable	Amount [kg]	3266.16
Recovered	Amount [kg]	2824.06

Table 2.6: Amounts and recovery rates of recovered materials from BET in the hydrometallurgical and pyrometallurgical cases.

Recovered material		**Hydrometallurgical case**	**Pyrometallurgical case**
Al	Recyclable [kg]	1086.17	1086.17
	Recovery rate	93.8% from cells / 95.5% from the rest	93.6% from cells / 95.5% from the rest
Cu	Recyclable [kg]	425.04	425.04
	Recovery rate	93.8% from cells / 76.3% from the rest	93.6% from cells / 76.3% from the rest
Steel	Recyclable [kg]	2634.28	2634.28
	Recovery rate	86.8%	86.8%
Co^{II}	Recyclable [kg]	490.31	490.31
	Recovery rate	93.6%	93.6%
Ni^{II}	Recyclable [kg]	489.39	489.39
	Recovery rate	93.6%	93.6%
Mn^{II}	Recyclable [kg]	477.50	477.50
	Recovery rate	93.6%	93.6%
Li^{I}	Recyclable [kg]	350.35	0
	Recovery rate	93.6%	0%
Recyclable	Amount [kg]	6040.59	5690.24
Recovered	Amount [kg]	5477.47	5149.54

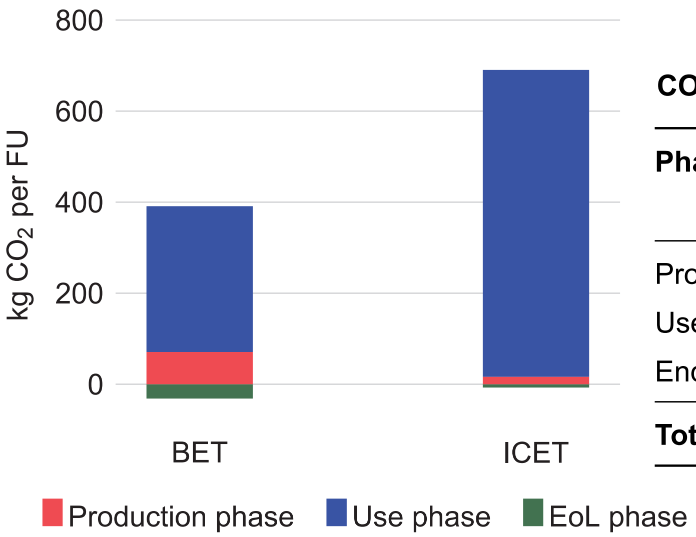
3 Results

Once the Life Cycle Inventory (LCI) is established, containing all elementary flows relevant to both trucks technologies, the next step is to evaluate the contribution of each elementary flow in terms of environmental impact. This is the purpose of Life Cycle Impact Assessment (LCIA) [17].

The study will primarily be focus on climate change impact.For the climate change impact assessment, the IPCC 2021 GTP 100 method has been used, because its primary focus is on Global Warming Potential (GWP). This impact category, is developed by the Intergovernmental Panel on Climate Change (IPCC) which is the international body for assessing the science related to climate change [34].This method evaluates the Global Temperature change Potential for a time horizon of 100 years. Furthermore, this method provides results in CO_2 equivalent units, which facilitates clear interpretation and comparison of climate impacts from different vehicle technologies.

As shown in Figure 3.1, BETs emit 47% less CO_2 compared to the ICETs. In both technologies, the use phase is the dominant contributor, accounting for the 89% of the total emissions in the BET and the 99% in the ICET.

Although the production phase in the BET generates more than four times the emissions of the production phase in the ICET, its overall CO_2 emissions are lower, due to the use phase. Recycling has a greater impact in the BET due to the presence of the battery pack, which increases the benefits of the end-of-life phase. Despite this, the overall production and end-of-life phase is higher for the BET.



CO_2 emissions per phase (per FU)

Phase	**BET** [kg CO_2] (%)	**ICET** [kg CO_2] (%)
Production	70.8 (20%)	16.2 (2%)
Use	320.34 (89%)	674.4 (99%)
End-of-Life	-31.5 (−9%)	-7.3 (−1%)
Total	359.6	683.3

Figure 3.1: Comparison of CO_2 emissions per functional unit (FU) for BETs and ICETs in the production, use and end-of-life phase. Negative values are preserved to reflect real contributions of each phase.

3.1 Climate change break-even

In this section, the emissions of both technologies are analyzed over the entire life cycle period, based on the distance driven. At 0 km, BET has a higher overall emissions due to the difference between production and end-of-life phase.

In this study, both electricity mix, diesel production and truck exhaust emissions are assumed constant over the total 1.300.000 km, meaning that future developments are not considered. The break-even point is at 111.420 km, after which the cumulative emissions for BEV Truck become lower than ICE Truck cumulative emissions. If we do not consider the recycling process at the end-of-life phase, the break-even point will increase to 200.570 km.

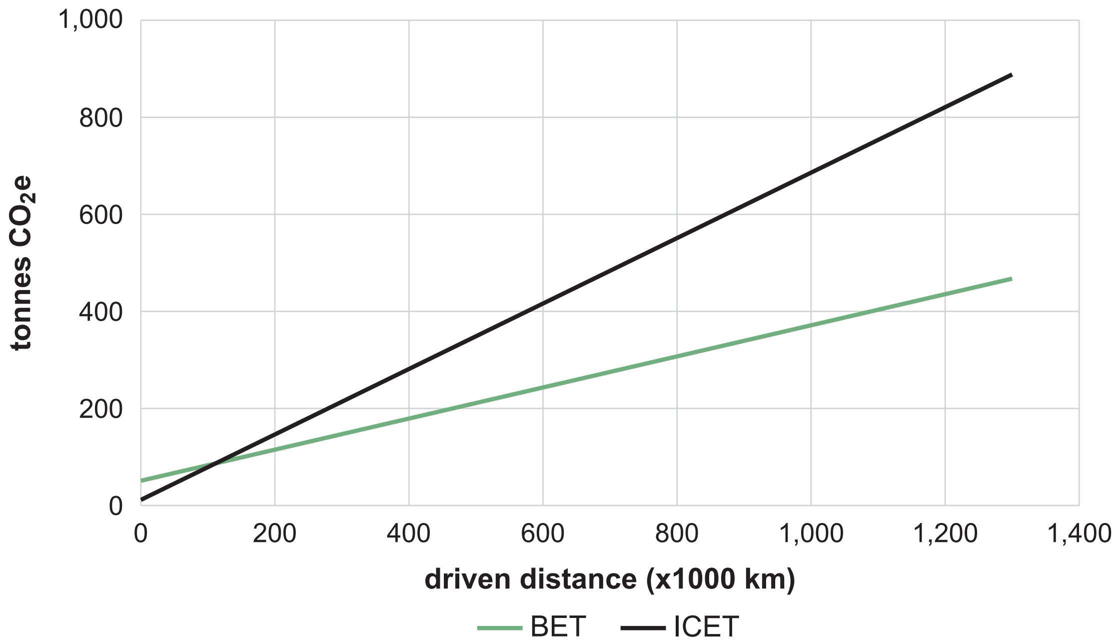


Figure 3.2: Cumulative CO_2 equivalent emissions over lifetime distance. BET has lower overall emissions after 111.420 km.

3.2 BET Analysis

In this section, the results for the BET are analyzed in detail. As it can be appreciated in Figure 3.3, the battery pack is the main contributor in the production phase, accounting for the 76% of total emissions. The tyres are the second largest contributor, with a share of 11.6%.

The CO_2 emissions in the use phase are totally dependent in the European Union electricity mix, highlighting the importance of decarbonizing the electric grid.

The end-of-life phase CO2 are negative, meaning that are avoided emissions. In this phase, the hydrometallurgical process contributes 51.2% and aluminium recycling contributes to 40.9%, highlighting the importance of battery cell recycling but also, aluminium recycling. A comparison between the hydrometallurgical and pyrometallugical recycling process will be conducted.

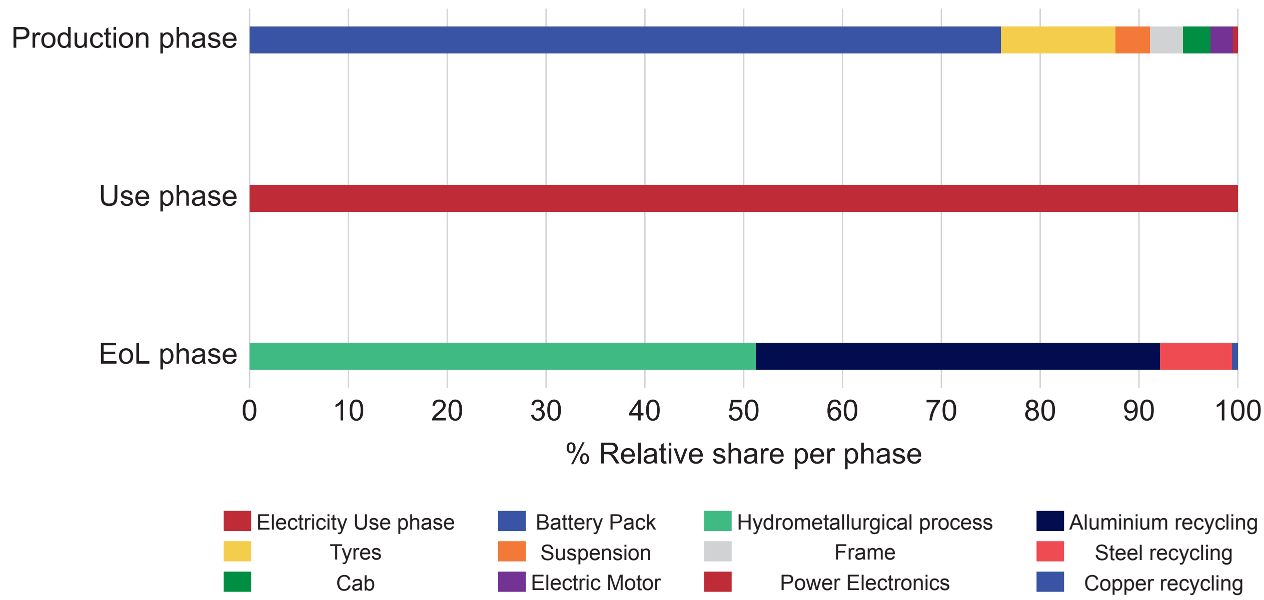


Figure 3.3: BET first-tier contribution. The main contributor of each phase are battery pack, electricity and battery recycling, respectively.

3.2.1 Battery Pack

The battery pack is the main contributor to CO_2 emissions in the production phase. Therefore, a tiered contribution analysis has been carried out. As outlined in the LCI, the battery pack consists of battery cells and the non-cell components, which includes materials required for packaging and protecting the cells. As shown in Figure 3.4, the battery cells account for 58.6% of the overall emissions of the battery pack, while the electricity required for assembly contributes 23.7%.

Within the battery cells, the main contributor to emissions is the cathode production, accounting for 66% of the emissions at battery cell level,and 38.6% of the total battery pack emissions. The second-largest contributor is the aluminium production, with a 11.2% share at battery cell level and 6.6% overall. Electricity use contributes 3.8% to the total emissions.

Focusing on cathode production, the primary contributor is Cobalt Sulfate responsible for 19.3% of the overall emissions. Electricity is the second-largest contributor, accounting for the 7.4% of total battery pack emissions.

From this section, the following conclusions are reached:

- Electricity accounts for 34.9% of the total CO_2 emissions from the battery pack.
- Cobalt sulfate and aluminium are the materials that contribute the most to the overall emissions, with shares of 19.3% and 17.1%, respectively.
- Battery cells are responsible for 58.6% of the total emissions.

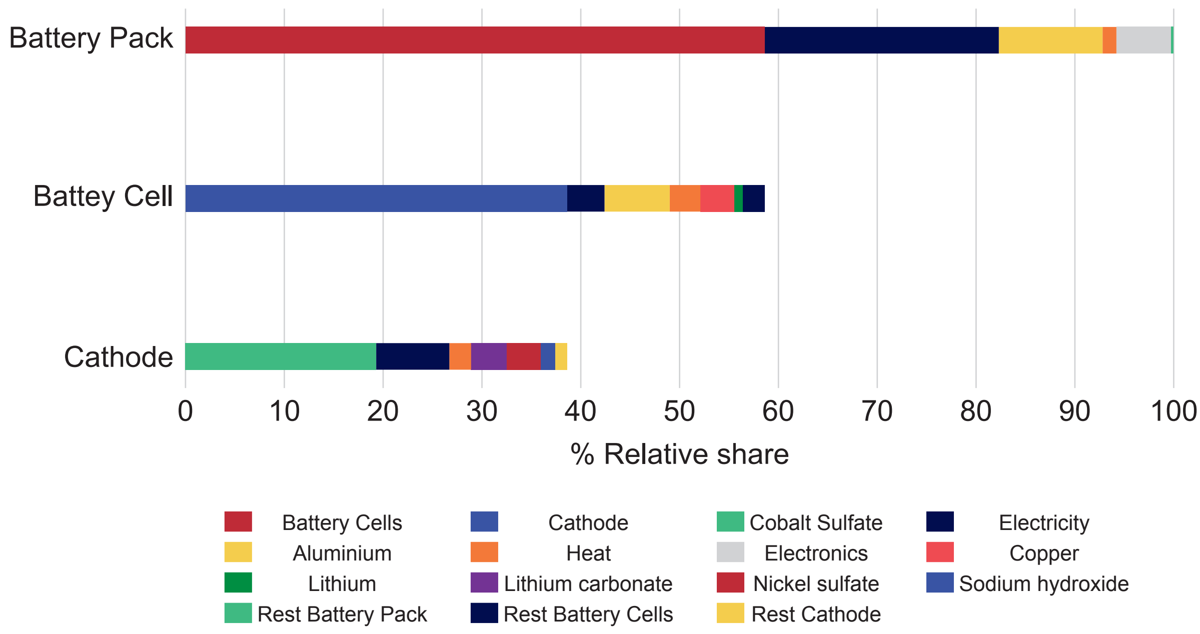


Figure 3.4: Battery Pack Tier Contribution

3.2.2 Hydrometallurgical vs Pyrometallurgical recycling process

As shown in Table 3.1, the overall emissions per functional unit of battery cells are lower for the hydrometallurgical recycling process. This process consumes 82.6% less electricity and additionally recovers lithium carbonate, which contributes to the 11.3% of the overall emissions.

These factors explain why the hydrometallurgical process achieves around 20% higher emission reductions than the pyrometallurgical process.

From now on, the hydrometallurgical recycling process will be adopted as the end-of-life strategy for the BEt, due to its lower environmental impact and its ability to recover a wider range of materials.

Table 3.1: CO_2 emissions by process for Hydrometallurgical and Pyrometallurgical Recycling

Process	**Hydrometallurgical (kg CO_2)**	**Pyrometallurgical (kg CO_2)**
Cobalt Sulfate	-9.68	-9.68
Aluminium	-3.21	-3.21
Lithium Carbonate	-1.83	0
Nickel Sulfate	-1.74	-1.74
Copper	-1.22	-1.22
Non Fe-Co metals	1.08	0
Electricity	0.20	1.15
Rest	0.23	1.18
Total	**-16.2**	**-13.5**

3.3 ICET Analysis

In this section, the results for the ICE Truck are analyzed in detail. As shown in Figure 3.5, the tyres and the engine are the main contributors in the production phase, accounting for the 35.6% and 20.1% overall emissions in this phase, respectively.

During the use phase, the main contributor to CO_2 emissions is the exhaust emissions from the truck, responsible for 80% of the total emissions in this stage. This highlights the importance of exploring alternatives that reduce exhaust emissions, such as the use of alternative fuels.

In the end of life phase, the main contributor is aluminium, that it was also the second highest contributor in the EoL phase of BET, with a share of 66.3%.

From this analysis, the following conclusions are reached:

- Exhaust emissions account for 79% of the total CO_2 emissions over the entire life cycle.
- Tyres are the main contributor in the production phase due to the shorter life cycle period compared to the truck itself.
- Aluminium reciclyng plays a key role in reducing environmental impact for both truck technologies.

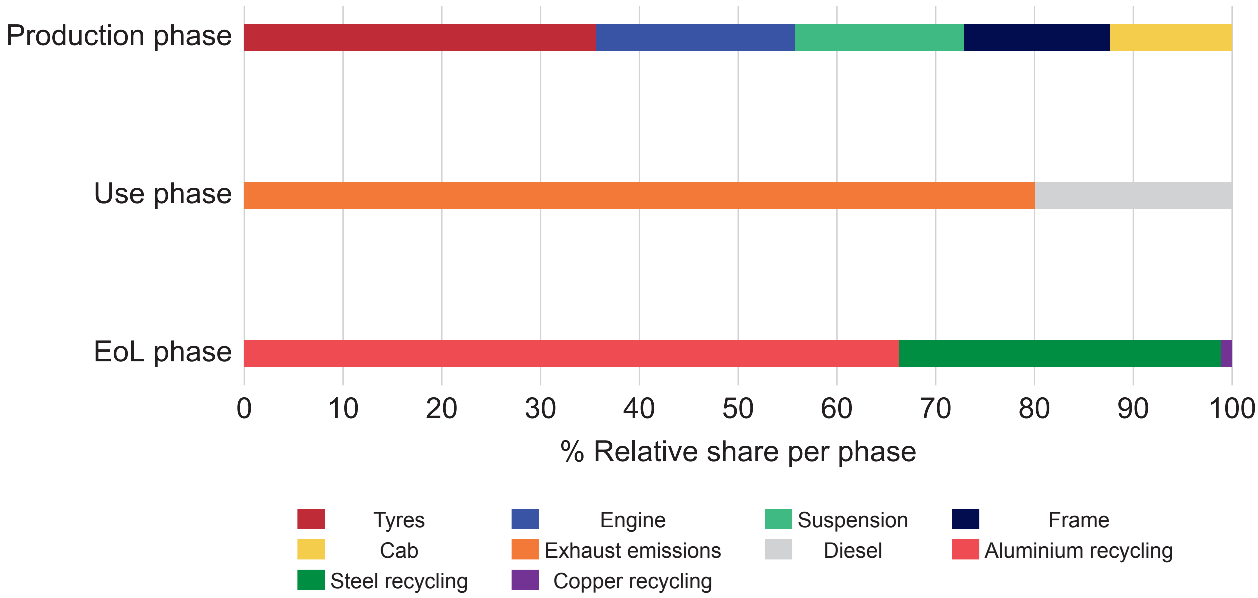


Figure 3.5: ICET first-tier contribution. The main contributor of each phase are tyres, exhaust emissions and aluminium recycling, respectively.

4 Sensitivity Analysis

4.1 Electricity mix

Electricity is a key contributor to the overall life cycle emissions of the truck, not only during the use phase but also in the production and end-of-life stages. This analysis aims to evaluate the emissions reduction potential when transitioning from current electricity mix to a net-zero electricity mix in all phases of the life cycle.

As shown in Figure 4.1, the electricity supply have a strong influence on the total life cycle emissions of the BET. The 0% scenario represents the current electricity mix, while the 100% scenario corresponds to a fully decarbonized, net-zero electricity mix. In the 100% reduction scenario, the overall emissions are reduced by approximately 95%. In the same way, a 50% reduction in the electricity supply, results in a 48% decrease in total emissions. Based on these two examples, an almost linear relationship can be observed between electricity grid carbon footprint and truck overall emissions, which means, that a minimum change in the electric grid carbon footprint can significantly impact the environmental performance of the truck.

Although the use phase is the phase that is more affected by these changes, the production phase also has a potential for reduction of 30% in the 100% reduction scenario, a point to take into account. In contrast, the end-of-life phase there is only a 3% improvement margin, mainly due to the implementation of the hydrometallurgical recycling process instead of the pyrometallurgical recycling process, which consumes more electricity. It is important to highlight that the impact of electricity mix reduction depends on the country where the vehicle operates. For this reason, another analysis has been carried out.

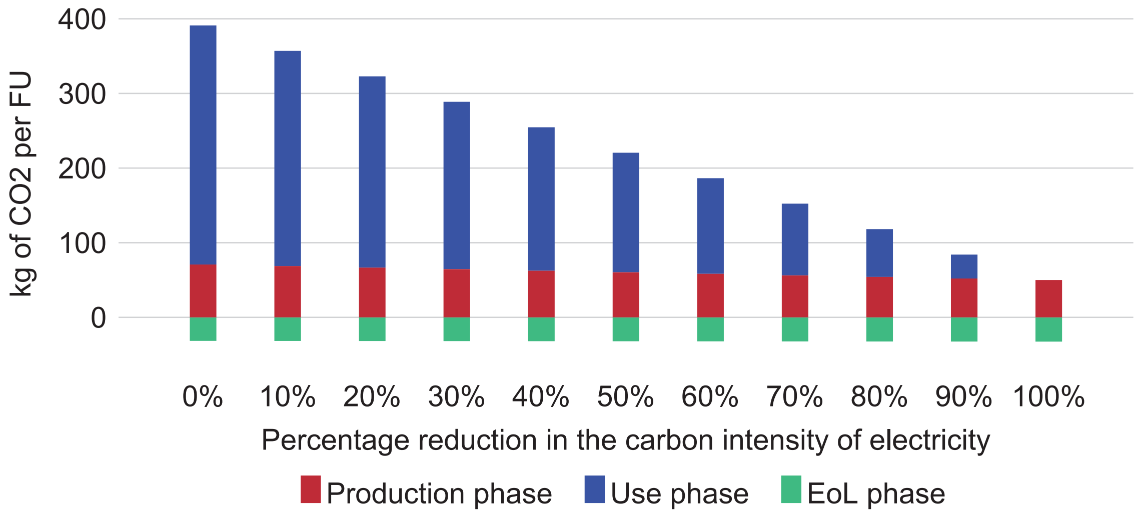


Figure 4.1: Overall CO_2 emissions of BET considering reductions in electricity carbon intensity

The use phase of the BEV Truck is modeled using the average electricity mix of Europe, as the study focuses on operations within Europe. However, the carbon intensity of the electricity mix varies significantly between countries, meaning that the overall CO_2 emissions of the BEV truck through its lifetime will depend on where the vehicle operates. [6]

To illustrate this, a sensitivity analysis was conducted using the electricity mixes of selected European countries. As shown in Figure 5.7, while the production and end-of-life phases remain constant, the emissions from the use phase will depend on the country. For example, countries like Poland and Germany are dominated by high-carbon electricity sources, while countries like France, Sweden and Norway benefit from cleaner, low-carbon energy mixes. These variations in electricity supply are reflected in the emission from the use phase. The total emissions for a truck that operates in Norway are 95% lower compared to a truck that operates only in Poland.

This highlights the importance of all countries transitioning to low-carbon electricity sources, as it can have a significant long-term impact.

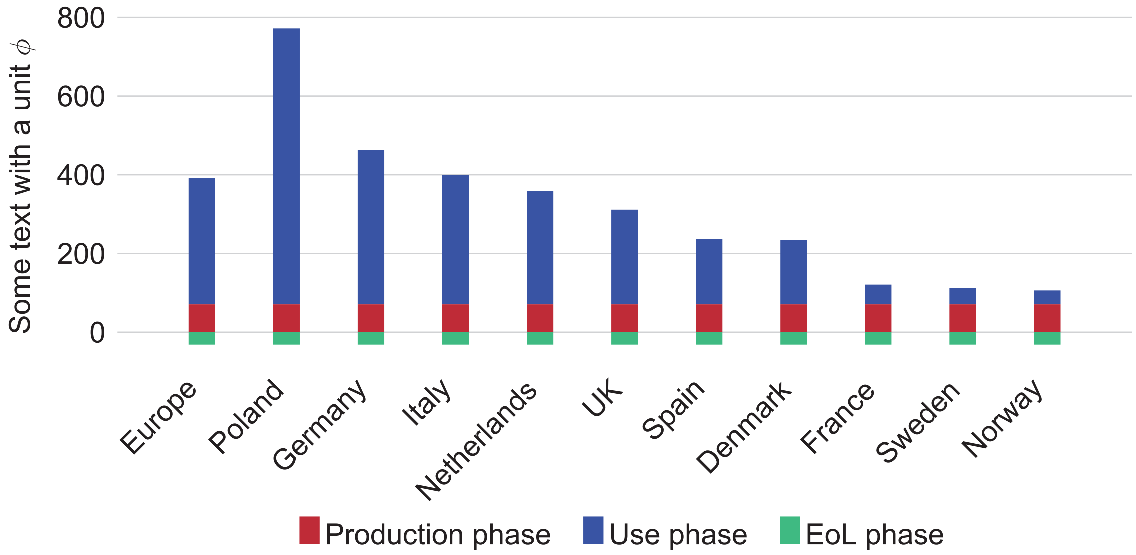


Figure 4.2: Overall CO_2 emissions per FU of BET across different european operating countries

4.1.1 Monte Carlo simulation

As discussed in the previous section, the total carbon footprint of an electric truck can vary significantly depending on the country in which it operates, as each nation has a different carbon intensity associated with its electricity grid. For this reason, a Monte Carlo simulation was conducted to capture and quantify this geographic variability in a probabilistic manner.

The Monte Carlo method is a way to estimate how a system might behave by running many random trials. Instead of solving complex equations exactly, this method generates lots of possible scenarios based on probability, helping to understand the range of possible outcomes and their likelihood [35]. In this case, it is applied to simulate the carbon footprint of the BET multiple times, where in each iteration the truck is assumed to operate in a different country, selected based on its relative importance.

To carry out this simulation, carbon intensity data (gCO_2/kWh) was collected for 26 European countries [28]. However, since not all countries have the same industrial and logistic influence in Europe, each country was weighted according to its total electricity consumption in 2023, according to the following report [36]. This approach ensures that countries with higher energy demand, more likely to host logistics activity, are given greater weight in the simulation.

Using this data, a weighted average and weighted standard deviation of the carbon intensity were calculated and used to define a log-normal distribution. This distribution realistically reflects the variability in carbon emissions during the truck's use phase. Based on this, 2000 random iterations were generated to simulate different operational scenarios.

Based on the carbon intensity values (in gCO_2/kWh) of 26 European countries and their respective share of total energy consumption in 2023, a weighted average and weighted standard deviation were calculated to reflect the actual operational distribution of the electric truck in Europe.

The weighted mean was computed as:

$$\mu = \sum p_i \cdot x_i \tag{4.1}$$

where x_i is the carbon intensity of country i, and p_i is the proportion of total energy consumption in that country.

The weighted variance is calculated as follows:

$$\sigma^2 = \sum p_i \cdot (x_i - \mu)^2 \tag{4.2}$$

and the weighted standard deviation:

$$\sigma = \sqrt{\sigma^2} \tag{4.3}$$

The resulting values are:

- Weighted mean: 242 gCO_2/kWh
- Weighted standard deviation: 160.41 gCO_2/kWh

To use these values in a Monte Carlo simulation, a log-normal distribution has been selected. A log-normal distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed. A random variable which is log-normally distributed takes only positive, which is essential to this context, as negative emissions from electricity is not quite realistic [37]. This distribution is particularly well-suited for modeling environmental variables that are strictly positive and exhibit an asymmetric distribution, such as energy consumption, carbon emissions, or the carbon intensity of electricity grids. These types of data tend to cluster around lower values but often have a long tail to the right, reflecting the presence of specific cases with significantly higher emissions, such as Poland, while other countries present much lower values, like France or Sweden.

The parameters of the log-normal distribution were calculated as:

$$\sigma_{\text{ln}} = \sqrt{\text{ln}\left(1 + \left(\frac{\sigma}{\mu}\right)^2\right)} = \sqrt{\text{ln}\left(1 + \left(\frac{160.41}{242.0}\right)^2\right)} = 0.6035 \tag{4.4}$$

$$\mu_{\text{ln}} = \text{ln}(\mu) - \frac{1}{2} \cdot \sigma_{\text{ln}}^2 = \text{ln}(242.0) - \frac{1}{2} \cdot (0.6035)^2 = 5.3069 \tag{4.5}$$

These parameters were used to generate 2000 random values of gCO_2/kWh from a log-normal distribution in the Monte Carlo simulation:

$$X = \exp\left(\mathcal{N}(\mu_{\ln}, \sigma_{\ln}^2)\right) \tag{4.6}$$

The following graph shows the probability distribution of carbon footprint values in the electricity grid, as obtained from the Monte Carlo simulation.

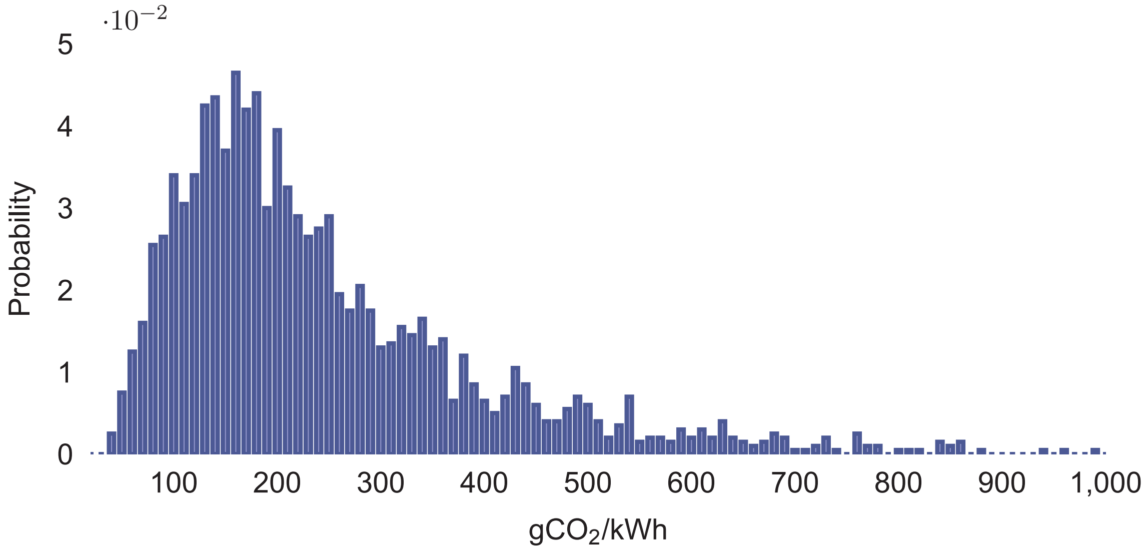


Figure 4.3: Probability distribution of carbon intensity values (gCO_2/kWh) obtained from the Monte Carlo simulation.

The graph shows that most of the carbon footprint values are concentrated between 100 and 250 gCO_2/kWh, with fewer cases reaching higher values. This indicates that the majority of the electricity mix in Europe is relatively low in emissions, but there are still some countries with much higher carbon intensities that cause the long tail on the right. The shape of the distribution reflects the differences in how electricity is produced across countries.

4.2 Life cycle period

The life cycle period influences the FU in the production and end-of-life phase.The use phase is not affected, because the FU is based on a fixed driven distance. The impacts in these two phases are determined by the ratio FU/life cycle distance. This study aims to highlight how variations in the life cycle period can affect overall emissions. In this case, a 1.300.000 km life cycle period has been selected as the baseline. In the scenario of life cycle period 1.000.000 km, overall emissions increased by 3.3%, while extending the life cycle distance to 1.500.000 km reduces the overall emissions by 1.5%.

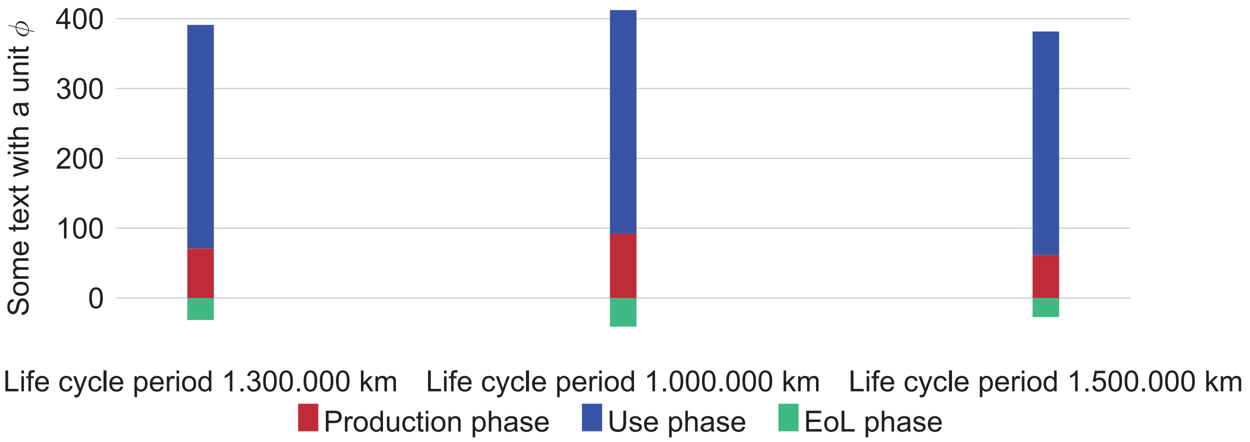


Figure 4.4: Stacked column chart

5 Prospective LCA

Until now, an environmental impact analysis have been conducted for both, diesel and electric trucks, based on a reference scenario, where emissions from production, use, and end-of-life phases were assumed to occur within the same time frame and under fixed conditions.This section assesses how the carbon footprint of BET could change in the future. For this reason, a Prospective Life Cycle Assessment (pLCA) will be carried out comparing two different future scenarios. In addition, in this chapter, a first-tier contribution analysis is performed to evaluate the impact of each main truck component. Additionally, a process contribution analysis is carried out to examine how factors such as electricity supply and manufacturing processes evolve over the years.

Prospective Life Cycle Assesment is a method used to evaluate the future environmental performance of current and emerging technologies in the future [38]. In this study, a prospective Life Cycle Inventory (pLCI) is applied to forecast the environmental impact of BET from 2020 to 2050. There are two approaches in prospective inventory modeling, background system and foreground system. [39]

5.1 Background System

Background systems provide contextual information for the analysis by modelling the upstream and downstream processes in which the technology operates. This data is typically obtained from LCI databases which provides aggregated data [40]. This analysis is conducted using premise (PRospective EnvironMental Impact asSEsment), an open-source Python library that modifies background LCI databases by integrating scenarios generated by Integrated Assessment Models (IAM). The outcome of IAMs is a detailed description of various potential future scenarios, each based on different assumptions and policy choices. These models incorporate assumptions about factors such as policies, socio-economic trend and technological developments. These assumptions are align with Shared Socio-economic Pathways (SSPs) and Representative Concentration Pathways (RCPs). SSPs describe different trajectories for the development of society and ecosystems in the next 100 years [41]. Using premise, the following SSPs scenarios can be generated [42]:

1. SSP1 or ”Taking the Green Road” scenario reflects an optimistic trend for human development, characterized by significant investments in education and health, rapid economic growth and effective institutions, driven by sustainable practices [43].
2. SSP2 or ”Middle of the Road” scenario, believes that historical patterns of development are maintained in the 21st century [43].
3. SSP5 or ”Taking the Highway” scenario also follows an optimistic trend for human development, as SSP1, but in this case, this progress is based on a fossil fuels economy [43].

RCPs are pathways whose main objective is to illustrate how greenhouse gas concentrations change over time [44].

In the Table 5.1, all the scenarios which can be generated with premise, combining SSP and RCP, will be shown. The base scenarios, do not follow any climate policy. There are two different scenarios, in case, it follows the Paris Agreement, PkBudg1150 and PkBudg500 . These scenarios differ from the cumulative carbon emissions cap, 1150 gigatonnes and 500 gigatonnes of CO_2, respectively. In the table can also be found the Global Mean Surface Temperature (GMST) increase by 2100, for each scenario.

Table 5.1: Overview of SSP/RCP scenarios, GMST increases by 2100, climate policies, and REMIND model versions

SSP/RCP scenario	GMST increase by 2100	Climate policy	REMIND
SSP1-None	2.3–2.8 °C	None	SSP1-Base
SSP1-None	∼2.2 °C	National Policies Implemented (NPI)	SSP1-NPi
SSP1-None	∼1.9 °C	Nationally Determined Contributions (NDCs)	SSP1-NDC
SSP1-RCP2.6	∼1.7 °C	Paris Agreement objective	SSP1-PkBudg1150
SSP1-RCP1.9	∼1.3 °C	Paris Agreement objective	SSP1-PkBudg500
SSP2-None	∼3.5 °C	None (eq. to RCP6)	SSP2-Base
SSP2-None	∼3.3 °C	National Policies Implemented (NPI)	SSP2-NPi
SSP2-None	∼2.5 °C	Nationally Determined Contributions (NDCs)	SSP2-NDC
SSP2-RCP2.6	1.6–1.8 °C	Paris Agreement objective	SSP2-PkBudg1150
SSP2-RCP1.9	1.2–1.4 °C	Paris Agreement objective	SSP2-PkBudg500
SSP5-None	∼4.5 °C	None	SSP5-Base
SSP5-None	∼4.0 °C	National Policies Implemented (NPI)	SSP5-NPi
SSP5-None	∼3.0 °C	Nationally Determined Contributions (NDCs)	SSP5-NDC
SSP5-RCP2.6	∼1.7 °C	Paris Agreement objective	SSP5-PkBudg1150
SSP5-RCP1.9	∼1.0 °C	Paris Agreement objective	SSP5-PkBudg500

In this case, two different scenarios from REMIND will be implemented: ”SSP2 Base” and ”SSP1-PkBudg1150”. ”SSP2 Base”, represents a conservative pathway without climate policy constraints, where future development follows historical trends.”SSP1-PkBudg1150”, on the other hand, illustrates an optimistic scenario aligned with the Paris Agreement. This version was chosen over PkBudg500 as it is considered more realistic. From now on, ”SSP2 Base” scenario will be referred as SSP2 and ”SSP1-PkBudg1150” as SSP1.

5.1.1 Premise methodology

Based on prospective scenarios generated by the REMIND and IMAGE models, premise increases the extent of prospective scenarios reaching different version of the ecoinvent database and multiple industry sectors, including power generation, cement, steel and fuel production [38].

The figure below illustrates the workflow used to generate a prospective life cycle inventory (LCI) database. In Step 1, integrated assessment model (IAM) scenarios are combined with a baseline LCI database (such as ecoinvent) to provide future-oriented inputs. Step 2 involves applying the premise tool, which uses the wurst library [**wurst**], to implement various transformations on the LCI database based on the selected scenario. This results in a modified version of the database that reflects a specific future year. In Step 3, the updated database is exported into a format compatible with common life cycle assessment tools, such as the Activity Browser, in our case. Lastly, Steps 4 and 5 focus on calculating environmental and resource indicators through LCA, which can then be used to inform or refine IAM outputs.

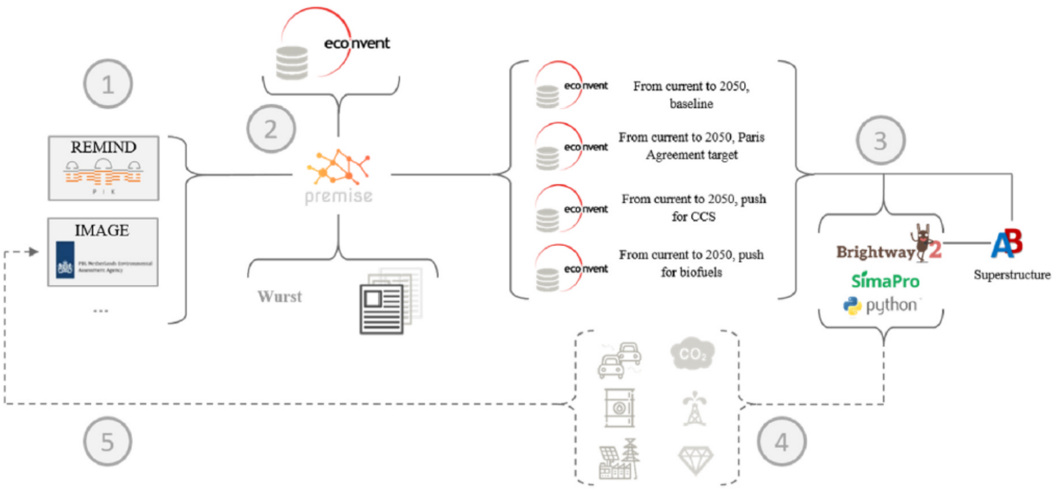


Figure 5.1: IAM–LCA integration scheme [38]

5.1.2 Premise transformation

As mentioned before, premise modifies the background system of LCA databases (such as ecoinvent) to reflect future scenarios derived from Integrated Assessment Models (IAMs), such as REMIND or IMAGE. These transformations are time and region dependent, meaning impacts vary by year and geographic location.

It transforms processes related to [38]:

1. Electricity generation
2. Steel and cement production
3. Fuel production
4. Transport
5. Battery cells production

In the case of battery production, Premise accounts for improvements in cell energy density by adjusting the mass of the battery cells accordingly. For NMC 111 battery cells, which are used in this study, the specific energy density increases from 0.18 kWh/kg to 0.20 kWh/kg, a 10% improvement, which translates into a 10% reduction in cell mass per kWh [45]. Also, the battery production will be affected by electricity generation and some process efficiency, among others.

In the case of steel production, premise modifies several fuel inputs for primary production processes, such as those found in pig iron and steel production datasets [45]. For secondary steel production, Premise adjusts the electricity input, reflecting the use of electric arc furnace (EAF) technology [45]. Similar to battery production, steel production is also affected by changes in electricity generation, among other factors.

5.2 Foreground system

Foreground data refers to the parts of the system that are directly related to the specific technology being assessed [39]. It usually includes the main processes and material or energy flows of this technology, usually based on experiments or detailed models [40]. To build future scenarios, methods such as learning curves, are implemented, to estimate how the system might develop over time. Typical sources of data for modelling the foreground include scientific publications, patents, expert opinions, experimental results, and process simulations [39].

In this study, only the background system will be considered for the prospective LCA study, due to time constraints. However, the foreground system is still mentioned, as it plays a relevant role for prospective LCA studies.

5.3 BET Results

5.3.1 SSP2 Scenario

In the SSP2 scenario, there is almost linear decrement in the carbon footprint with a total reduction of 77% from 2020 to 2050, going from 400.38 kg CO_2 to 92.6 kg CO_2 overall per FU. The production phase is reduced by 40%, the use phase by 79% and the end of life by 26%. There is a direct relation between production and end of life phase, where always the avoided emissions of the recycling process are between the 40% and 50% of overall production emissions.

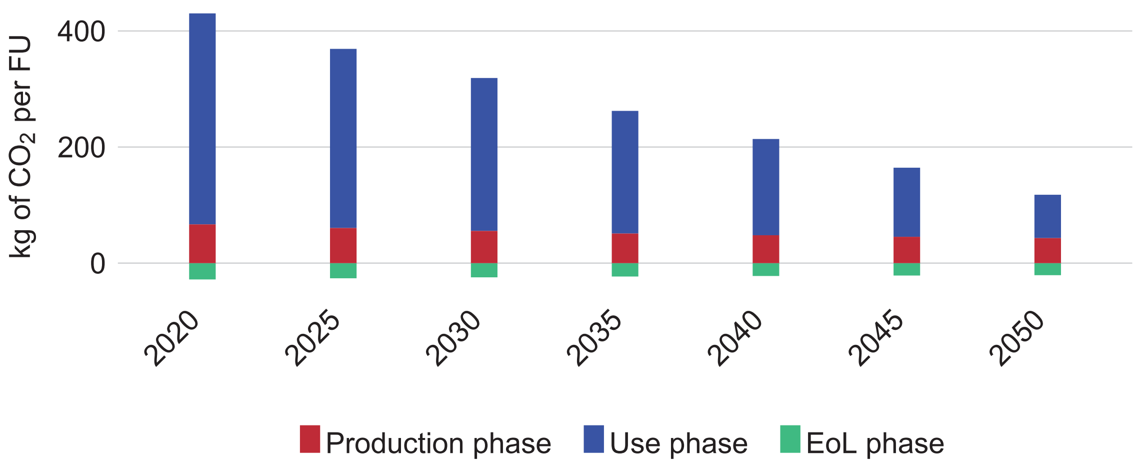


Figure 5.2: SSP2 CO_2 emissions from 2020 to 2050 per FU

Production phase analysis

In the production phase, overall emissions are reduced by 40%. The main contributor to the footprint at this stage is the battery pack, which shows a 44% reduction in emissions from 2020 to 2050, as shown in Figure 5.3. These changes are due to modifications in the background system, which is why a process contributor analysis will be carried out.

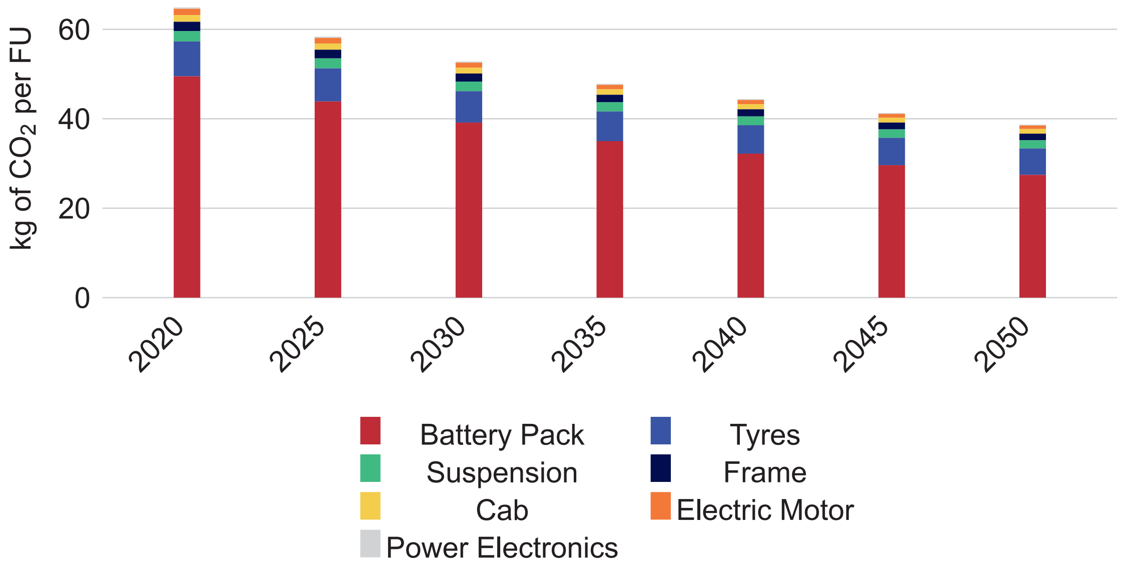


Figure 5.3: SSP2 first-tier contribution from 2020 to 2050 in production phase

As shown in Figure 5.4, the main contributing process in this phase is electricity. With a reduction of 68% , it significantly drives the overall 40% decrease in emissions. Natural gas emissions are reduced by 6%, while heat from non-natural gas sources decreases by 8%. Emissions from black carbon production remain constant over time, and the carbon footprint of pig iron production is reduced by 15%. In conclusion, under the SSP2 scenario, electricity plays the most significant role in reducing emissions during the production process, while other processes, such as heat, show only minor improvements.

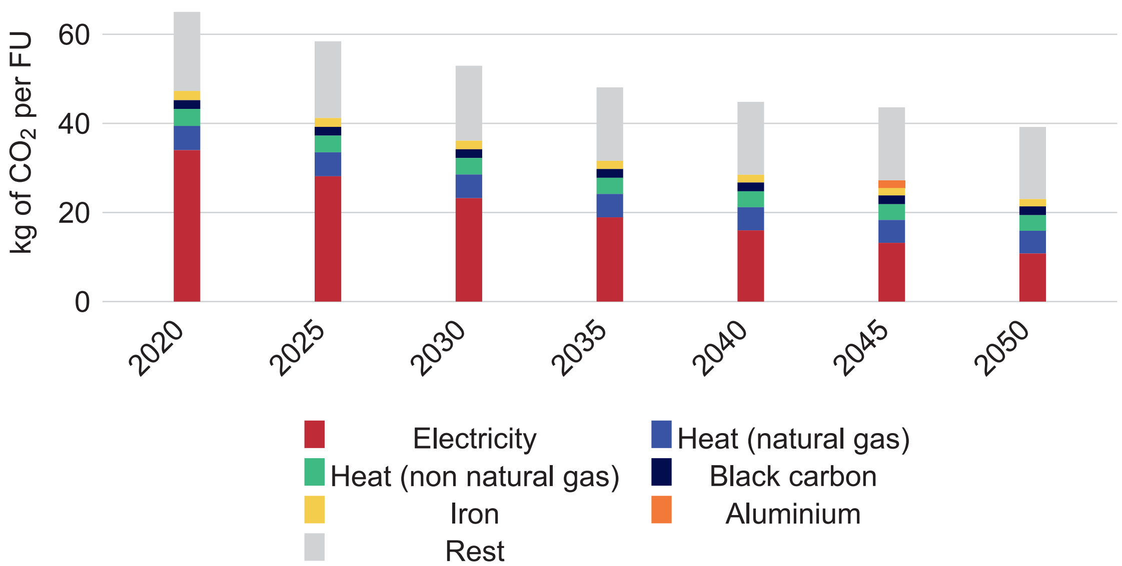


Figure 5.4: SSP2 process contribution from 2020 to 2050 in production phase

End-of-Life Analysis
In this study, the end-of-life phase refers to avoided emissions as a result of the recovery of certain materials. At first, it may seem intuitive that, as the production and use phases

improve their performance by reducing emissions, the avoided emissions are going to increase. However, it is the other way around.

In this phase, avoided emissions are reduced by 26%. The main contributor is the hydrometallurgical process used for battery recycling, which only achieves a 16% reduction. In contrast, the aluminum recycling process shows the largest reduction, at 43%. This is likely due to the fact that primary aluminum production has become cleaner over time, resulting in lower avoided emissions from recycling. A process contribution analysis has also been carried out.

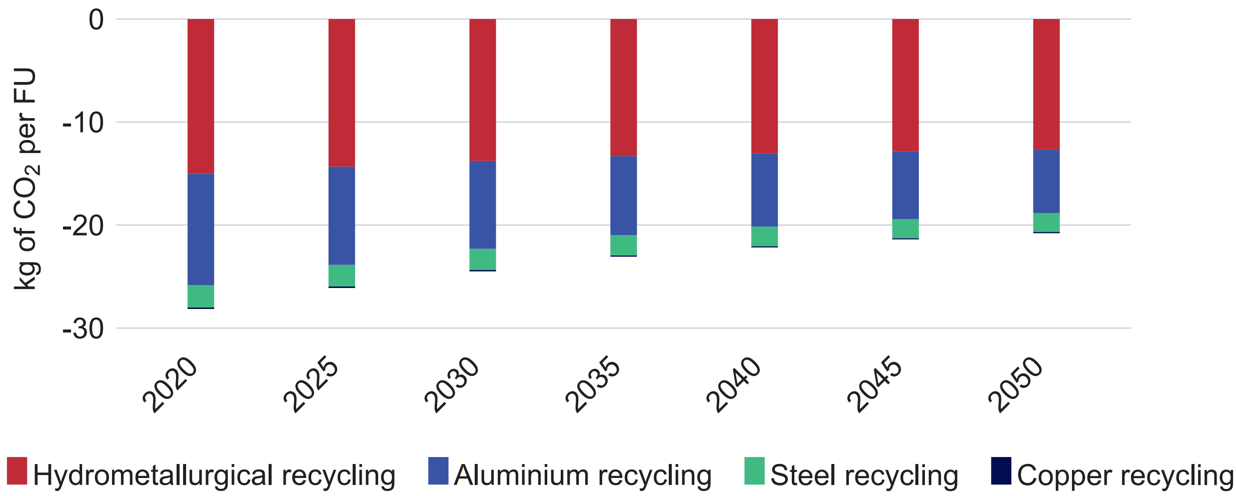


Figure 5.5: SSP2 first-tier contribution from 2020 to 2050 in end-of-life phase

As shown in Figure 5.6, the main source of avoided emissions is electricity, with a reduction of 60%. However, as electricity generation becomes cleaner over the years, the associated avoided emissions decrease, leading to a lower overall contribution in this phase. The other processes remain largely constant, except for iron production, which shows a 7% reduction.

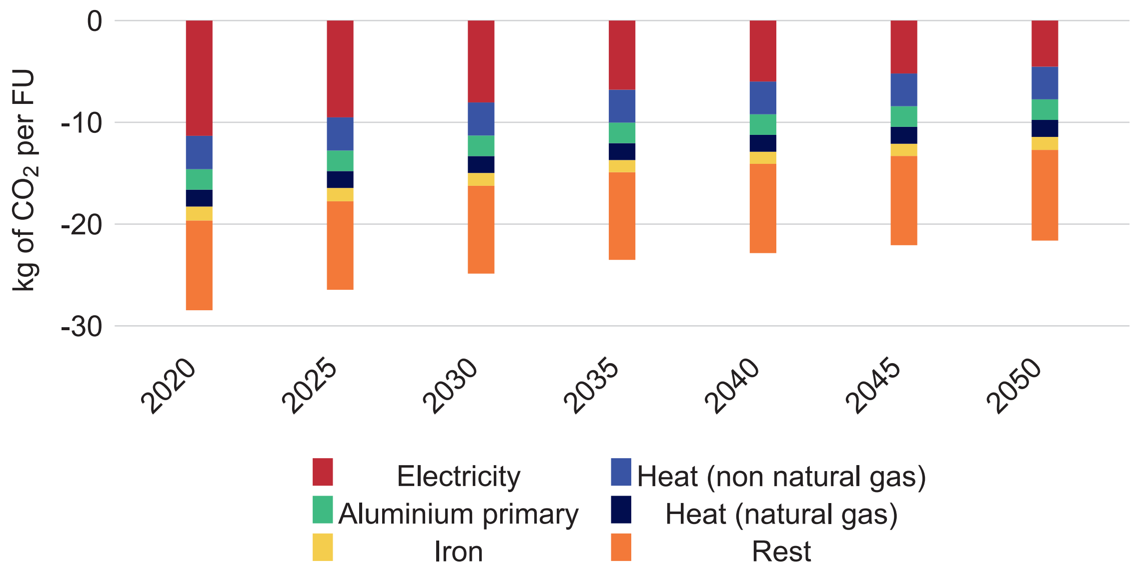


Figure 5.6: SSP2 process contibution from 2020 to 2050 in end-of-life phase

5.3.2 SSP1 Scenario

In this case, the SSP1 results are more favorable, as this scenario is more optimistic and driven by sustainable solutions. There is a 92% reduction in overall emissions from 2020 to 2050, following a negative exponential trend. Compared to the SSP2 scenario, the emission from the use phase is significantly lower, with reductions of 74%, 83% and 83% in 2035, 2040, and 2045, respectively. These findings highlight the importance of pursuing sustainable pathways and demonstrate how much the outcomes can change depending on the scenario.

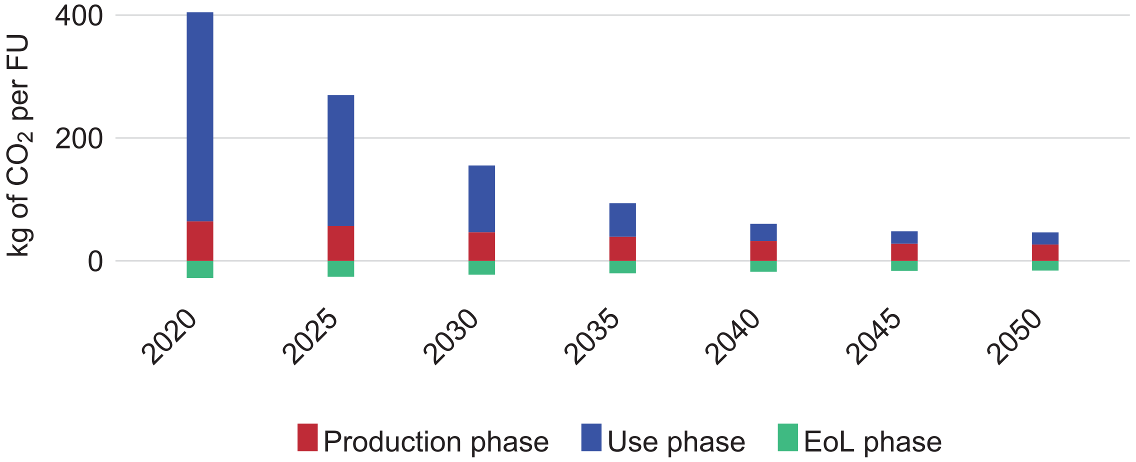


Figure 5.7: SSP1 CO_2 emissions from 2020 to 2050

The following figure illustrates the carbon intensity of electricity generation under both SSP1 and SSP2 scenario. The SSP2 pathway shows a linear decrease, dropping from 319 gCO_2/kWh in 2020 to 65 gCO_2/kWh in 2050. In contrast, the SSP1 scenario follows a negative exponential trend, consistent with previous SSP1 results, decreasing from 298 gCO_2/kWh to just 17 gCO_2/kWh over the same period.

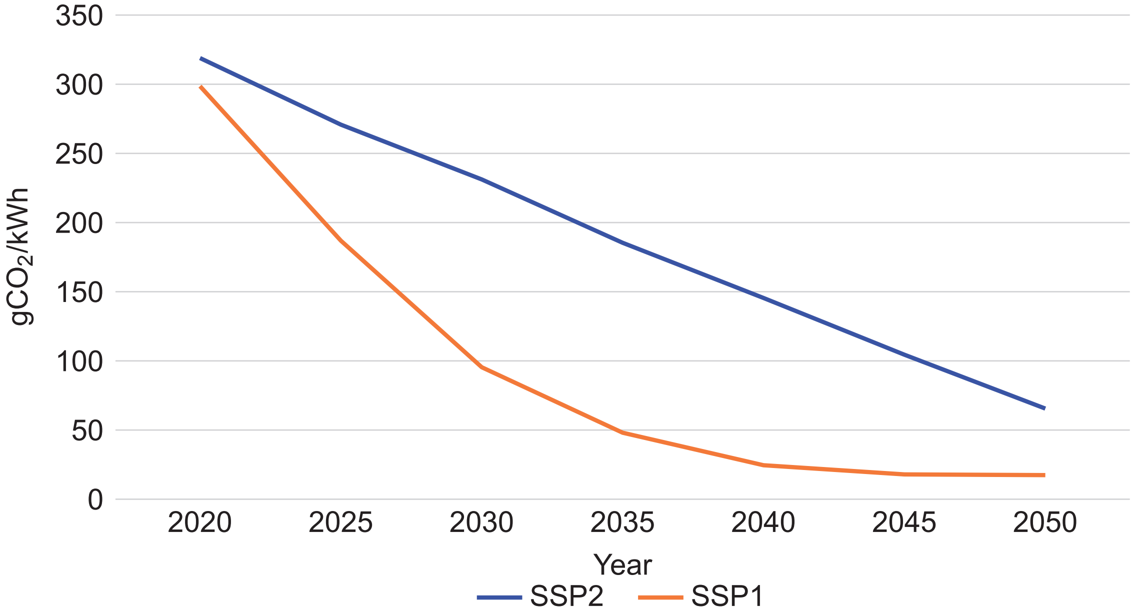


Figure 5.8: Projected electricity grid carbon intensity under SSP1 and SSP2 scenarios.

5.3.3 Roadmap emissions

There is a certain limitation with all results that have been reached: it is assumed that the production, use, and end-of-life phases occur within the same year or within a short, fixed time frame. This oversimplifies the reality, as it does not reflect the full life cycle of a truck, which spans several decades. However, since the environmental impacts of these three phases are known from 2020 to 2050, it is possible to generate results closer to reality.

In this case, the overall life cycle emissions of three electric trucks are compared: one manufactured in 2020, one in 2030, and one in 2040. For all three cases, a 10-year operational lifetime is assumed, with an annual driving distance of 130,000 km.

For the truck manufactured in 2020, it is assumed that it enters operation in 2021, operates until 2030, and is recycled in 2031. Since data is only available for the years 2020, 2025, and 2030, the following assumptions are made for the electricity mix during the use phase: from 2021 to 2024, the 2020 electricity mix is used; from 2025 to 2029, the 2025 electricity mix is used; and for 2030, the 2030 mix is applied. The recycling process in 2031 is modeled using 2030 conditions. These same assumptions are applied to the trucks manufactured in 2030 and 2040, using the corresponding future electricity mixes for each operational period.

In this case, the results for the SSP2 scenario are compared. The truck manufactured in 2020 shows total life cycle emissions of 476.867 kg of CO_2. The 2030 truck emits 335.766 kg of CO_2, which represents a 30% reduction compared to the 2020 case. The truck manufactured in 2040 has the lowest emissions, with a total of 204.764 kg of CO_2, corresponding to a 57% reduction compared to the 2020 truck. As shown in the graph, the production phase presents smaller differences, with a 19% reduction for the 2030 truck and a 32% reduction for the 2040 truck compared to the 2020 case. The operational phase shows the greatest impact, driven by the improvement in the electricity mix over the 10-year intervals between the trucks. Regarding the end-of-life phase, the largest improvement is observed for the 2020 truck, as it has the greatest potential for avoided emissions, as previously discussed.

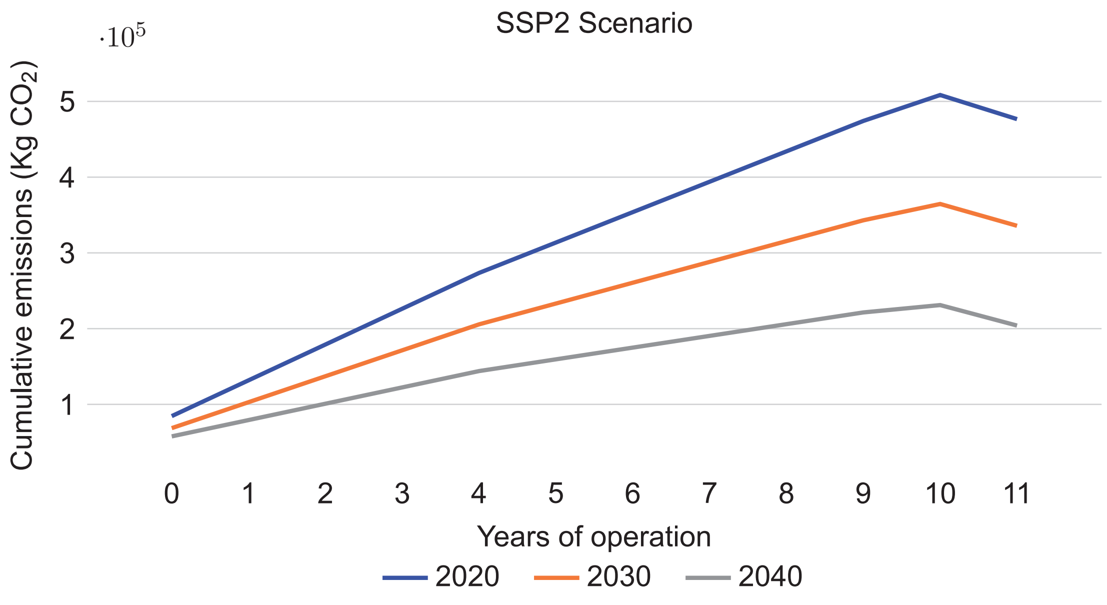


Figure 5.9: Cumulative carbon emissions over time for electric trucks manufactured in 2020, 2030, and 2040 under the SSP2 scenario.

In the SSP1 scenario, the contrast between the trucks is more pronounced due to the exponential decline in the carbon intensity of the electricity mix. The total emissions for the 2020 truck are 383.874 kg of CO_2, while the 2030 truck emits 132.976 kg, representing a 65% reduction compared to 2020. For the 2040 truck, total emissions drop even further to 51.832 kg of CO_2, an 86% reduction compared to the 2020 scenario. It is worth noting that, the total emissions of a truck manufactured in 2030 under SSP1 conditions are lower than those of a truck manufactured in 2040 under the SSP2 scenario. This shows how climate policies or decisions toward a more sustainable trajectory can have a significant long-term impact.

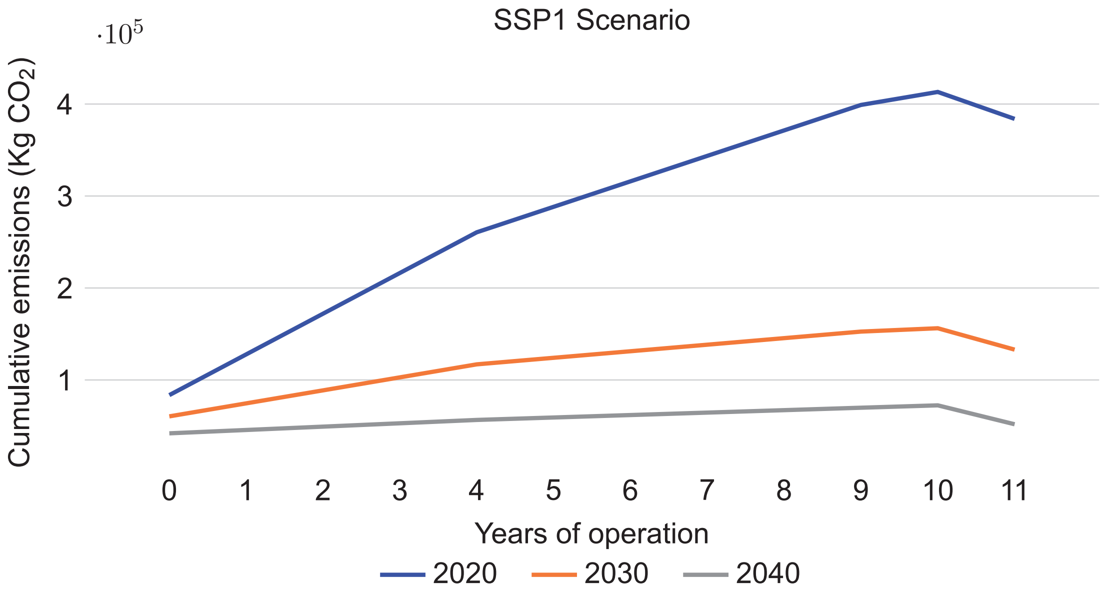


Figure 5.10: Cumulative carbon emissions over time for electric trucks manufactured in 2020, 2030, and 2040 under the SSP1 scenario.

The conclusions of this section show that the use phase plays a fundamental role in the total carbon footprint and it directly depends on the carbon intensity of the electricity grid. This, in turn, largely depends on the energy policies and commitments of each country's government. To establish this new electric mobility, continuous investment in sustainable solutions is essential, not only in technology but also in a competitive charging infrastructure, along with strong adoption and investment from transport companies in BEV Trucks.

6 Conclusions

After considering the reference scenario for both diesel and electric truck and dynamic scenario for the electric truck, the following conclusions are reached:

- In the reference scenario, although the production phase of the electric truck results in over four times higher CO_2 emissions compared to the diesel truck, the total life cycle emissions of the electric truck are 47% lower. This is largely due to the use phase, where the electric truck emits 53% less, directly depending on the electricity grid mix in the region where it operates.
- Recycling also contributes to reducing the carbon footprint by avoiding the extraction of new raw materials in both vehicle types. In the case of the diesel truck, the reduction is approximately 1%, while for the electric truck it reaches 9%, primarily due to battery recycling, which accounts for over 50% of the avoided emissions in this phase.
- This study compares hydrometallurgical and pyrometallurgical battery recycling technologies, concluding that the hydrometallurgical process is more favorable due to its ability to recover lithium and its lower energy consumption.
- The electricity mix plays a fundamental role throughout the life cycle of the electric truck, not only during the use phase, but also in the production and end-of-life stages. If CO_2 emissions from electricity were reduced by 100%, the total carbon footprint of the electric truck would decrease by 95%. In a scenario with a 50% reduction in grid emissions, total life cycle emissions would still drop by 48%.
- Not all countries share the same electricity mix. This high sensitivity to the grid means that the country where the truck operates significantly affects its environmental performance. To address this uncertainty, a Monte Carlo simulation was carried out, using the electricity mix and energy consumption of different European countries. The resulting average emission intensity ranged between 150 and 250 gCO_2/kWh, reflecting the regional variability.
- Throughout the electric truck's life cycle, certain phases, particularly the use phase and production phase, show high vulnerability to external factors such as the electricity mix and technological context. This highlights the importance of decarbonizing the power sector and advancing battery recycling technologies to maximize the environmental benefits of electrification.
- In the prospective LCA, a clear contrast emerges between a conservative future scenario based on historical trends (SSP2) and a sustainability-oriented scenario (SSP1) that assumes stronger commitments to green solutions. A truck manufactured in 2020 under the SSP1 scenario emits 19% less CO_2 compared to SSP2. However, for a truck produced in 2040, the difference grows significantly, SSP1 results in 75% lower emissions. This highlights the critical importance of advancing toward a more sustainable future and shows how climate policies or decisions toward a more sustainable trajectory can have a significant long-term impact.
- In both scenarios, a clear relationship can be seen between the emissions from the production phase and the avoided emissions in the end-of-life phase. If production emissions are reduced by 40% between 2020 and 2050, the avoided emissions

at end-of-life also decrease by 24%, because producing materials becomes more efficient over time, meaning that what is avoided through recycling has a lower environmental impact each year.This highlights that while recycling is important, it is equally essential to continue improving the production phase, as a cleaner production system also reduces the footprint at the vehicle's end of life.

7 Future work

As a suggestion for future work, additional truck technologies could be considered for comparison, including hydrogen powered trucks or hybrid configurations combining diesel and electric powertrains. Another suggestion would be to simulate how the carbon footprint of freight transport could evolve by gradually introducing BETs into the transportation system up to 2050, based on projected emissions from the prospective LCA.

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