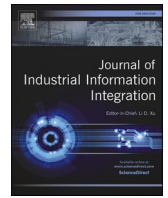




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Full Length Article

Eco-design tool to support the design of industrial electric vehicles. The case studies of an electric shuttle and an autonomous mobile robot

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ABSTRACT

The benefits of process optimization brought by multiple tools that appeared in shopfloors with the fourth industrial revolution are undiscussed; however, they need electricity to run and require critical materials. Additionally, the significant impact on sustainability that early design decisions can have over the entire lifecycle is well-recognized. The literature counts several environmental analyses of electric vehicles but narrows almost uniquely on passengers' cars. Currently, the literature should i) widen the range of analyzed products, ii) consider all stages of the product life cycle, iii) provide tools suitable for the early stage of design, able to return consistent results handling very little data. As electrification is concerned, in the literature there are approaches intended to assess the environmental impacts or focused on the design tool. The proposed approach, further applied to develop an eco-design tool, overcomes the existing literature by providing a tool i) able to handle few data, ii) that considers all the product lifecycle phases, and iii) allows designers to assess and compare alternative scenarios. A method is proposed, and a tool derived. Two applications concern an electric shuttle and an autonomous mobile robot; with the latter the gap of assessing the environmental impact of autonomous mobile robots is also filled. The obtained results are reasonably comparable with other existing works. Results are compared to a full LCA for the frame assembly and prove that i) the tool is reliable, and it more likely overestimates the impacts; ii) the design phase is subjected to high variability, and this affects the tool results. Future works may introduce additional types of batteries, deeper focus on the manufacturing phase; machine learning techniques may support future extension of the tool and create parametric models for conceptual and early design. The proposed method and tool can be extended to the economic sphere.

1. Introduction

The issues relating to environmental pollution, climate change, and natural resource scarcity underline the need for a drastic change of direction at both social and industrial levels, to preserve natural ecosystems and human existence. Nevertheless, this must cope with the constant technological development that is pervading private and industrial contexts. With the fourth industrial revolution, multiple tools have popped up in shopfloors, i.e., cobots (collaboration robots), Automatic Guided Vehicles (AGVs), Autonomous Mobile Robots (AMR) and highly automated lines. Certain cyber-physical systems (such as cobots, and autonomous vehicles) are seen as decisive contributions to addressing many societal challenges [1].

1.1. Industrial electric vehicles

The fourth industrial revolution has gradually introduced modernization in production facilities through the inclusion of automated and interconnected machinery and many digital technologies, such as big data analysis, information technology, Internet of Things (IoT) and Additive Manufacturing (AM) [2]. Industry 4.0 (I4.0) is also driving toward the computerization and automation of the supply chain: for example, the handling of materials is increasingly using mobile robots as AGVs or AMRs [3]. There are studies providing decision support systems for technology adoption in transport / mobility division within the context of Industry 4.0 [4]. The integration of EVs (Electric Vehicles), smart grids, and IoT technologies, using renewable energy resources towards green smart transportation became a hot topic [5]. The literature should examine a wide range of products because electrification

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affects many sectors and products beyond cars. The complex systems of perception, locomotion and navigation composed of many sensors and powerful processors allow the AMRs to continuously monitor the surrounding environment and internal systems. AMRs that can move freely within an industrial facility is increasingly in demand for industrial processes 24/7 [6]. They mainly contribute to the efficiency of warehouses, accelerating materials' handling [7] and the entire logistics chain. To accomplish the plant's needs at best, AMRs may be customized and made efficient, according to the tasks of a specific process.

Actions taken to improve the product lifecycle by an eco-design tool must be able to handle very little data while producing reliable results to be appropriate for the first design phase and cover each stage of the life cycle. Liu and De Giovanni [8] examine a dynamic supply chain model in which a supplier decides both the wholesale price and the investment in green process innovation while a manufacturer sets the retail price. AGVs are among the innovative technologies discussed, but the environmental impact analysis in this case is often very general and more oriented to economic aspects. The study proposed by Graba M. et al. [9] is oriented to analyze only the sustainability of the use phase of an AGV and therefore aims at optimizing the traveled path. As with cars, also for AGVs [10] the information that can be used for an environmental impact analysis may be partial or missing for the first design phase. As a result, it is hard to assist designers in making decisions and assess decisions they make when changes can still be made. However, it urges to make them gain an in-depth understanding of environmental impacts throughout the life cycle, under various conditions, and compare alternatives.

1.2. The claim from the design

The great technological innovations increase the complex characteristics of manufacturing systems [11] with consistent contribution to process optimization. Nevertheless, these solutions need electricity and require critical materials. It is, therefore, necessary to review the design of these products, focusing on sustainable development. Early design decisions can have a very significant impact on sustainability [12] of material and manufacturing phase and the product's entire life cycle [13], including End of Life (EoL), logistics, and maintenance. The need to consider environmental impacts next to traditional design criteria (e. g., operational performance and costs) requires the design team to be able to evaluate the environmental performance of many alternative concepts [14]. The present paper focuses on a method to support the design of industrial EV, which represent a product category significantly affected by the environmental issue.

As EVs' emissions are not eliminated but allocated upstream of the fuel cycle and downstream on materials, production, and EoL processes [15], several environmental sustainability analyses focus only on certain lifecycle phases [16,17]. For example, Chi et al. [18] developed a new scheme for the energy management of parallel hybrid vehicles. Countless are the comparative analyses between traditional and electric cars [19]. However, the literature lacks studies focused on industrial EVs. Moro et Helmers [20] proposed a hybrid method that keeps the main hypotheses of the Well-to Wheel (WTW) methodology but integrates them with LCA data restricted to the Global Warming Potential (GWP). The work focuses on general EVs, presents narrow boundaries and is restricted to carbon footprint quantification. If other impact categories' damages were quantified, adverse results may be reached [20]. Nordelof et al. review 79 works with the purpose to investigate the usefulness of different types of LCA studies of EVs to provide robust and relevant stakeholder information. They distinguish WTW studies, complete LCAs, and battery LCAs. They outlined a strong focus on light passenger vehicles and greenhouse gas emissions [21]. In addition to that, any purpose for supporting the design phase has not been highlighted. Many studies relate to the evaluation of the environmental impact of EV and their comparison with a traditional combustion engine, but the methods proposed are not intended for the early design stages when little data are

available. The literature needs a streamlined environmental evaluation tool for the early stages of the design process to i) support designers in decision making and evaluation of their choices [22] and ii) provide a complete overview of the environmental impacts throughout the life-cycle. Literature should:

- Enwide the range of analyzed products, because electrification is a topic that is pervading many sectors and products not only with passenger vehicles
- Consider all stages of the product life cycle
- Provide tools suitable for the early stage of design, and thus able to return consistent results handling very little data.

1.3. LCA, eco-design and EVs

The advantages of electric mobility are still under debate, because of the offset between higher production impacts and a more efficient use phase, and because of the role played by the electricity mix used to recharge vehicles. Table 1 summarizes the main literature outcomes concerning the environmental assessment of vehicles (mostly EVs), their comparison with other vehicles (mostly Internal Combustion Engine Vehicles – ICEVs), the availability of eco-design tools intended to support the design of EVs.

In the literature, LCA analyses of EVs are usually coupled with comparisons with LCA analyses of ICEV. A key success factor for bringing LCA to early design stages is the way results of environmental evaluations are visualized. Design processes are complex itself and conducting LCA is also a complex task. Merging these two processes by adding the right theory will lead to a successful integration of LCA into early product design stages [27]. Parametrization might be useful when developing design tools [26].

A clear gap is the lack of design tools intended for EVs, regardless of their use. From the literature emerges that either there are approaches intended to assess the environmental impacts of an EV, or the focus is on the design tool; however, eco-design approaches either focus on batteries' design or are developed for products of different nature. Their applicability to a wider range of products may be difficult as eco-design tools often rely on previous product analysis to provide quantitative results. Whenever results are compared, the juxtaposition is made between BEVs and ICEVs. Therefore, a wide gap is identified, as contributions focused also on other kind of EVs (i.e., industrial vehicles, electrified system for goods transportation) are missing.

1.4. Scope

In this context, the goal of the present paper is to provide a simplified and flexible predictive method for environmental analysis that considers every phase of the whole life cycle and supports the designers in quantitatively evaluating the consequences of their choices. Thus, the method aims to provide support to the designer in the early design phase, estimating the environmental burden of an EV (EV involves cars and other vehicles). On the contrary, the proposed tool can be applied to any type of vehicle and considers all the main aspects of the life cycle. The case studies allow to verify the potential of the proposed tool, the results and possible scenarios that can be extracted. The proposed approach overcomes the existing literature filling the main gaps:

- It is the base to develop tools able to handle few data and be suitable for the very early stage of design
- It ensures designers the possibility to assess and compare alternatives head in time in the product lifecycle
- It accounts all lifecycle phases
- The derived tool is intended for industrial EVs; however, it is applicable to a wider range of EVs
- The application of the tool to the case of an AMR fills the gap concerning the assessment of the environmental impact of AMRs.

Table 1

Main consistent results for evaluation of environmental impacts of EVs. The absence of tools intended for the design phase that encompass all the lifecycle phases is clear.

Authors	Design Tool	Lifecycle stages	Vehicle / component	Comparison	Main proposal
Raugei et al. [16]	–	Cradle to Grave	compact passenger vehicles	–	Complete and fully consistent LCA-based comparison of a range of light weighting options for compact passenger vehicles.
Raugei et al. [17]	–	Cradle to Grave	Battery	–	Flow diagram of the main steps in the manufacturing of a complete Li-ion battery pack.
Ambrose et al. [15]	–	Cradle to Grave	BEV	ICEV	Examines trends in BEV design choices and use models to examine the potential effects on lifecycle GHG emissions of BEV
Petrauskienė et al. [19]	–	Cradle to Grave	BEV	ICEV	Rely on data of common products released on the market to collect data for their inventory.
Burchart-Korol [23]	–	WTW	BEV	ICEV	Focus on energy used to charge EV batteries in the present and future (Poland and Czech Republic).
Collado-Ruiz et al. [24]	–	Cradle to Gate + EoL	Battery	–	Method/guide for selecting priorities or key strategies, starting from analysis of similar products. Not suitable for feedback of actual product performance.
Marmiroli et al. [25]	–	Cradle to Gate + Use	Light duty vehicles	ICEV (CNG*, diesel)	Comparison of LCA of light-duty vehicles for transport of goods in urban environments. Use of primary data from the manufacturer and ad hoc kinematic model
Ostad-Ahmad-Ghorabi et al. [26]	x	Cradle to Cradle	–	–	3 steps- parametrization based on design parameters to conduct LCI
Ostad-Ahmad-Ghorabi et al. [27]	x	Cradle to Cradle	–	–	Integration of LCA into early product design stages
Lavrador and Arioli de Sá Teles [28]	–	Cradle to Cradle	Vehicle	ICEV	Comparison LCA between EV and ICEV running with bioethanol from sugarcane cultures
Xia et al. [29]	–	Cradle to Cradle	Vehicle	ICEV	Review of BEVs and ICEV vehicle full LCA
Epp et al. [30]	x	–	Battery	–	High-Voltage-Battery-Optimization-Tool (HV-BOT) focused on batteries design.
Wang et al. [31]	x	Cradle to Cradle	Battery	ICEV	Analysis tool providing insights into material consumptions and environmental impacts of SiNW-and SiNT-based batteries. LCA results are normalized per km of EV driving distance.
Picatoste et al. [32]	x	Cradle to Cradle	Battery	–	List of CE design criteria for LIBs used in BEVs; Implementation potential evaluated according to the views of industrial stakeholders.

* CNG= Compressed Natural Gas.

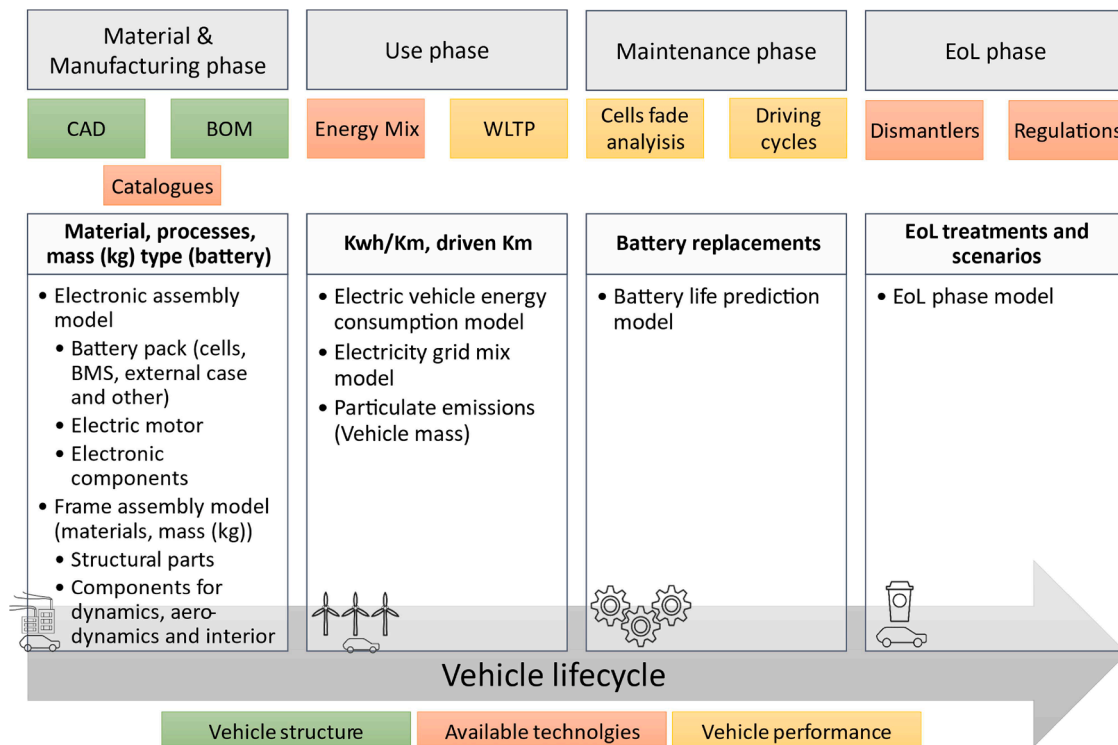


Fig. 1. Method proposed. Bold boxes contain the characteristic parameters for the lifecycle phases. Colored boxes contain possible sources for input data: green boxes refer to the structure of the vehicle; orange boxes refer to the technologies that can interfere with the model; yellow boxes refer to the performance of the vehicle.

The tool allows for the implementation of a personalized driving cycle of the vehicle in terms of speed, distance and slope required, as well as to define different scenarios related to the workload; in this way, it will be possible to configure the best strategy, in detail the use phase of the vehicle to make it more efficient in the consumption of energy resources. The results obtained for the AMR contribute to create the currently almost inexistent literature concerning autonomous vehicles employed in smart manufacturing systems. Currently, solely the world of autonomous vehicles for passengers is widely explored [33], but they are likely part of a wider picture; consequently, they do not consistently relate to the FU. For example, in the dynamic LCA, LCI is integrated with the company's business intelligence by Ferrari et al. [34], where only the consumption of autonomous vehicles is considered.

The paper is structured as follows: Section 2 describes the proposed method, Section 3 introduces the tool developed from the method for the design of EVs and critically discusses it; Section 4 shows the result of the first implementations of the tool, that concerns an electric shuttle and an AMR; ultimately, the conclusion briefly summarizes the work.

2. Materials and methods

The proposed model is a simplified LCA methodology for estimating the environmental impacts of production and EoL of different types of EVs (e.g. AMR, AGV, shuttle, car, bus). The proposed approach is a flexible framework, which adapts to the level of detail and quality of the available input data. The model (Fig. 1) allows for consideration of process data, material mixtures and technologies, as well as a simplified LCA of vehicles using pre-configured modules [35].

This approach was chosen because the analysis is influenced by the use phase and the lack of a detailed LCI. Based on the available information, such as components, technologies and performance data, generic modules are scaled and adjusted according to calculated parameters and scaling factors, thus providing a reliable estimation of the environmental performance of vehicles with comparable technical specifications and dimensions. The proposed methodology is located at an initial design phase; therefore the approach is considered suitable.

The method is divided into four parts, which refer to the different models that are used to describe the phases of the boundaries of the system analysis: I) Material and Manufacturing phase model; II) Use phase model; III) Maintenance phase model; IV) EoL phase model. The use phase is defined as the sum of three different aspects, which are: the consumption of the energy carrier (electricity), maintenance and particulate emissions related to the consumption of wheels, road and brakes. The maintenance phase in this study is detached from the use phase, because it assumes a relevant role for EVs, especially when affected by the replacement of the battery pack.

2.1. Material and manufacturing phase model

EV modeling must be divided into two macro groups: Frame Assembly (FA) and Electronic Assembly (EA) [15]. The EA consists of modules and components often available in the main databases of LCA tools, which are parameterized. The FA is described as the set of parts and materials that have not been defined in the EA: not only the structural part of the vehicle but also all those components belonging to the dynamics, aerodynamics and interior of the vehicle.

2.1.1. Electronic assembly model

The main components of the EA are the battery pack and the electric motor, the remaining (i.e., inverters, cables) are indicated in a single group generically referred as electronic components. To identify the impacts of each component it is important to define the mass of each; this information is retrievable from catalogs. The battery pack can be divided into four macro-groups:

- Cells:

- type of cell, such as lithium-ion (Li-Ion); it is also useful to indicate the chemistry of the cathode in the case of Li-Ion batteries; this helps identifying the correct type of battery (use the standard Li-Ion battery, if the data is not available);
- number of cells in the battery pack;
- mass of the cell;
- cell model.
- External case:
 - mass;
 - material.
- Battery Management System (BMS): represents a part of the electronics of the battery pack.
- Other: in this group cables, generic electronic material, plastic and steel are inserted; the latter two materials are used for the structure supporting the cells.

2.1.2. Frame assembly model

The FA consists of defining the list and percentages of materials that make up the rest of the vehicle. This encompasses the entire vehicle without the EA. The total mass of the chassis assembly to which the percentages defined above will refer, are obtained by subtracting the average mass of the driver and the mass of the EA from the unladen mass of the vehicle [15]. The evaluation of the Material and Manufacturing phase is complete.

2.2. Use phase model

The energy consumption model aims to obtain the energy consumed per unit of distance traveled (kWh/km). Multiplying this value with the total distance traveled over the entire life of the vehicle allows to obtain the overall energy consumption needed to evaluate the environmental impact of the electricity consumed. The energy model is based on the methods proposed by Marmioli et al. [25], Hernandez et al. [36], and Faria et al. [37,38]. The literature agrees in creating a kinematic model, given that vehicle emissions and fuel consumption are characteristics largely depending on the type of vehicle and driving style. The driving style influences the performance. It is accounted by analyzing different driving cycles [39] taken from the Worldwide harmonized Light vehicles Test Procedure (WLTP) [40], considering different load percentages. Determined the average consumption, the specification distance traveled during the useful life of the vehicle leads to the total energy consumption.

2.2.1. Electric vehicle energy consumption model

The proposed energy model uses a kinematic approach, where the operating conditions of the system and the control variables are obtained from the kinematic state of the system. The power demand for the powertrain derives from the vehicle's speed models, which are considered as inputs for the kinematic model, considering the transmission efficiency chain and the efficiency of each machine (battery, DC/AC Inverter, electric motor, transmission). The total power required at powertrain level is the sum of several components, as rolling resistance, slope resistance and aerodynamic drag. The kinematic model is partially based on the study of Hernandez et al. [36]. The power required from the wheels is calculated for each time phase of the driving cycle, using Eq. (2.1)–Eq. (2.4):

$$F_g = m \cdot g \cdot \sin(\alpha) \quad (2.1)$$

$$F_{roll} = m \cdot g \cdot C_r \cdot \cos(\alpha) \quad (2.2)$$

$$F_{ad} = 0.5 \cdot \rho \cdot C_d \cdot A_F \cdot V^2 \quad (2.3)$$

$$F_{acc} = m \cdot a \quad (2.4)$$

Where, F_g is the slope resistance (N); F_{roll} the rolling resistance (N), F_{ad}

the aerodynamic resistance (N) and F_{acc} the force required by acceleration (N). m is the vehicle mass (kg), g the acceleration of gravity (m/s^2), α the angle of inclination and g the acceleration (m/s^2). C_r is the rolling resistance coefficient, ρ the air density (kg/m^3), C_d the drag coefficient, A_f the vehicle frontal area (m^2) and V the vehicle speed (m/s). The resolution of the calculation is second. Depending on requests and available data, a model can be created faithful to reality, with load (m) and path inclination variation (α). If no information is available, the average consumption should consider a flat path and different standard average loads (0 %, 25 %, 50 %, 75 %, 100 %, Eq. (2.5) and Eq. (2.6)).

$$F_{tot} = F_g + F_{roll} + F_{ad} + F_{acc} \quad (2.5)$$

$$P_{wheel} = F_{tot} \cdot V \quad (2.6)$$

Where F_{tot} is the total force (N) and P_{wheel} the wheels power required for $\alpha = 0$ (W). To obtain the required power to the battery pack it is necessary to apply filters and consider the correct yields referred to the powertrain (Table 2). First, the power required from the battery is calculated, by filtering the results obtained from the calculation of the power required to the wheels (Table 2, Filter 1).

The values of the power required to the battery must be greater than zero because the results of the calculation of P_{wheel} can be negative, this is due to the deceleration phases. From the filtered results ($P_{wheel,fp}$), the required power from the guide cycle is obtained (Eq. (2.7)):

$$P_{el,supply} = \frac{P_{wheel,fp}}{(\eta_t \cdot \eta_m \cdot \eta_c \cdot \eta_b)} + P_{aux} \quad (2.7)$$

Where, $P_{el,supply}$ is the power required to the powertrain; P_{aux} refers to the power required by auxiliaries; η_t is the efficiency of the transmission; η_m is the efficiency of the engine; η_c expresses the performance of DC/AC inverter; η_b is the performance of the battery. Compared to the formulation of Hernandez et al. [36] the contribution of battery efficiency has been added because it is responsible for the energy delivered. P_{peak} refers to the peak power that the electric motor can reach. The values above the peak will be placed equal to the peak, so that the vehicle can, as far as possible, follow the cycle. With this filter the $P_{el,supply,eff}$ are retrieved. EVs are usually equipped with a Kinetic Energy Recovery System (KERS), a key component for improving energy efficiency and positively influencing the vehicle environmental impact. To evaluate the benefit introduced by KERS, the negative data are considered ($P_{wheel,fn}$ in Table 2, Filter 3) and $P_{el,recover}$ counts the potentially recovered power according to Eq. (2.8):

$$P_{el,recover} = P_{wheel,fn} \cdot (\eta_t \cdot \eta_m \cdot \eta_c \cdot \eta_b) \cdot \eta_K \quad (2.8)$$

Where η_K is the yield of KERS. The results obtained must be filtered

Table 2
Filters.

ID Filter	Name Parameter Filtered	Filtered	Description
1	$P_{wheel,fp}$	$P_{wheel} \geq 0$	Required power greater than zero because of acceleration: power required and presence of energy consumption.
	$P_{el,supply,eff}$	$P_{el,supply} \leq P_{peak}$	The power actually required cannot exceed the peak power (maximum power that the engine is capable of delivering).
3	$P_{wheel,fn}$	$P_{wheel} \leq 0$	Power may be negative due to deceleration phases. This power is recovered by the KERS.
4	$P_{el,recover,eff}$	$P_{el,recover} \leq P_{rec,standard}$	The recovered power cannot be greater than the maximum that the battery is able to recover.

considering the maximum value of the charging power $P_{rec,standard}$. As data are negative, the sign of the maximum charging power is changed (Table 2, Filter 4). According to the convention for signs, the power values lower than the charging power will be replaced with the charging power value because it represents the minimum limit of power able to absorb. The values obtained are indicated as $P_{el,recover,eff}$. For each time step, Eq. (2.9) and Eq. (2.10) are valid:

$$P_{tot} = P_{el,recover,eff} + P_{el,supply,eff} \quad (2.9)$$

$$L_i = P_{tot} \cdot t_{step} \quad (2.10)$$

Where L_i (J) is the work required at t_{step} ; t_{step} (s) is the time step (always equivalent to one second in a guide cycle). Eq. (2.14) – Eq. (2.14) are explained as they are not present in the study by Hernandez et al. [36]. E_{tot} (kWh) is the total energy consumption of the entire life cycle, and it is given by Eq. (2.11), where d_{tot} (km) is the distance of the entire life cycle and C_m (kWh/km) is the average consumption per km (Eq. (2.12))

$$E_{tot} = C_m \cdot d_{tot} \quad (2.11)$$

$$C_m = \frac{E_{dc}}{d_{dc}} \quad (2.12)$$

Where d_{dc} (km) is the distance of the driving cycle path; E_{dc} (kWh) is the total energy consumption of the driving cycle (Eq. (2.13)) and L_{dc} (kJ) is the total work required during the driving cycle (Eq. (2.14)).

$$E_{dc} = 3.6 \cdot 10^{-3} \cdot L_{dc} \quad (2.13)$$

$$L_{dc} = 10^{-3} \cdot \sum_i^T L_i \quad (2.14)$$

2.2.2. Electricity grid mix model

Once defined the total consumption of electricity, the definition of the reference Electricity Grid Mix is needed. The Electricity Grid Mix is the set of primary energy sources used for the production of electricity supplied by sales companies to end customers. Traditional energy includes dirtier and inefficient energy sources, while modern renewable energy includes cleaner and more efficient energy sources [41]. In some cases, companies have a private photovoltaic system available to produce electricity. This obviously mitigates consumption from the national grid and consequently also the final impact. Therefore, for a correct assessment of the impact, it is necessary to distinguish the amount of electricity consumed by the national grid and that consumed by company's photovoltaic system. It is preferable to model the energy mix based on the supplier's energy mix, instead the average country mix.

2.2.3. Particulate emissions

A comprehensive assessment of the use phase's impact also involves the particulate emissions related to tires, road and brake consumption. The result depends on the mass of the vehicle and the distance traveled.

2.3. Maintenance phase model

The Maintenance phase is part of the Use phase; however, in the case of EVs as the present method, it is advisable to consider it separately as the battery replacement can significantly impact the overall lifecycle. The Maintenance phase consists of two main activities: the replacement of the battery pack and the standard routine maintenance operations on an EV. As the battery pack is concerned, its Material and EoL phases are considered, as it is produced with the purpose of replacing the old battery back. The environmental impact of the replaced battery pack is totally borne by its first life. The battery pack life prediction model counts the number of replaced battery packs. The standard routine maintenance operations are the cooling system maintenance, the wheels and braking system replacing.

2.3.1. Battery life prediction model

Literature is pervaded with multiple models estimating the life of a battery pack whose benchmarks are based on cell capacity fade analysis. The model of Wang et al. [42], derives from the observation of the results of the capacity fade analysis of a Li-Ion cell, model 26,650, with LiFePO4 cathode chemistry. Cui et al. [43] consider a study for a Li-Ion battery, prismatic and with LiCoO2 as cathode chemistry. Both of these models make it possible to calculate the loss of capacity of each individual cell. In this way, it is possible to derive the energy content for each cycle of the battery pack ($Ebat_i$) and get d_i (km) that expresses the current distance taken by exploiting the energy made available by the i th battery cycle (Eq. (2.15)); $Ebat_i$ (kWh) represents the total current energy of the battery for the specific i th cycle.

$$d_i = \frac{Ebat_i}{Cm} \quad (2.15)$$

The replacement of a battery pack takes place when its capacity falls below the established minimum value. The US Advanced Battery Consortium (USABC) standard for EVs suggests battery replacement when capacity reaches 80 % [44]. The battery pack catalogs links the percentage of capacity to the number of cycles. Through the knowledge of the energy content for each cycle, the total number of cycles, and the energy consumption of the vehicle, it is possible to obtain the distance traveled before replacing the battery pack (Eq. (2.16)).

$$d_{batt_tot} = \sum_i^{n(Q(80\%))} d_i \quad (2.16)$$

Where d_{batt_tot} (km) is the sum of the current distance exploiting all the battery cycles until the battery capacity falls to 80 %. Based on the estimated distance the vehicle can potentially travel, the number of battery pack replacement is given (A in Eq. (2.17)).

$$A = \frac{d_{batt_tot}}{d_{tot}} \quad (2.17)$$

2.4. End-of-life phase model

The modeling of the EoL phase consists in assigning the specific EoL treatment to each material and component. The ELV (End-of-Life Vehicles) directive raised the reuse and recovery rates to no less than 95 % [45]. A high share of the ELV returned would motivate manufacturers for applying design for environment strategies to reduce recycling costs [46]. Statistical results of high recycling rates have to be taken with a grain of salt (i.e., 97 % of recycling rates declared by Germany) as they do not include the destiny of the exported cars, in particular of those exported to countries outside Europe [47]; therefore, the default recovering percentages can conservatively be lower than those defined by the directive and declared for the European area [48].

3. Theory/Calculation

A tool has been created by following the approach proposed in Section 2. The tool is intended the very beginning of the design process, even when little data are available to characterize the product. In fact, standard values are suggested by default and may be utilized in the computation in the absence of any additional specific data. The tool is intended to be used in industrial settings by businesses smaller in size than the multinational auto manufacturers for the creation of EVs. The tool's key strengths will be used here: it introduces the concept of sustainability during the design phase and provides a preliminary quantitative comparison between various use scenarios. Regardless of applicability of integrated product development methods to integrate the conceptual design and preliminary design phases [49], the tool is easy to use and suitable also for both stages, prior the 3D modeling stage; in fact, suggestions are provided for some data. For instance, the choice

of the type of vehicle updates the total distance traveled over its lifetime; the number of battery cells is suggested according to the nominal cell voltage as unlikely is a known parameter because the battery is a commercial product and not produced by the EV manufacturer. The recommended driving cycle is based on the vehicle mass and motor peak output. Different driving cycles are available; however, the suggested one should be selected by the user's options. The tool is developed on Microsoft excel; the first sheet introduces the tool; the second is dedicated to data entering; a third sheet displays the results. According to the data available, the user can modify the supporting sheets (i.e., load and driving cycle). Those are devoted to the battery duration estimation, the evaluation of environmental impacts, and the evaluation of energy consumption with customized transport loads and guide cycles. The workflow of the tool goes through three steps: I) Input; II) Analysis; III) Output.

3.1. Tool structure

Fig. 2 depicts the three main components of the tool structure:

- Database (DB), which consists of Environment DB and Vehicle DB. The capacity of a Li-Ion cell's driving cycles and fading model are contained in the first; they are employed in the data processing, along with the data entered by the user. The vehicle DB allows for environmental analysis and contains the unitary impacts;
- Admin interface, in charge of data processing and environmental analysis.
- User interface, which addresses the input data entering and the output configuration; the user may select which driving cycle and load to show.

Examples of interfaces for driving cycles and analysis output are shown in Fig. 2. It also provides input and analysis data tables in a condensed form, for demonstration reasons. The tool's three primary processes (Input, Analysis, and Output) are detailed in the following paragraphs.

3.2. Input

The user enters all the data required for the analysis of each lifecycle phase in the first step. Some input parameters are directly used (Data Collection); others, need to be computed by the tool prior entering the analysis (Data Processing). The tool suggests input values as the information is gradually added; suggestions may be changed. The product function gathers broad data regarding the usage of the vehicle, such as the type of vehicle and its use, service days per week, years of supplied service, total traveled distance, maximum speed, and number of seats. The materials and parts of the vehicle are specified in the product structure. The method suggests dividing the material phase into EA and FA.

For the EA the main components are identified by specifying some of their characteristics:

- Battery pack (mass, number of batteries inside, battery efficiency, capacity, and nominal voltage):
 - Cells (number, capacity and nominal voltage of the cell, number of cycles per replacement);
 - Houses (type of material and its masses);
 - Battery Management System (BMS) (mass);
 - Other internal components (mass).
- Electric motor (number of motors, mass, efficiency, peak power);
- Electronic components (list of the other most important components, indicating the mass and relative efficiency, e.g., converter, weight, and efficiency).

The main materials are identified for the FA, and their mass

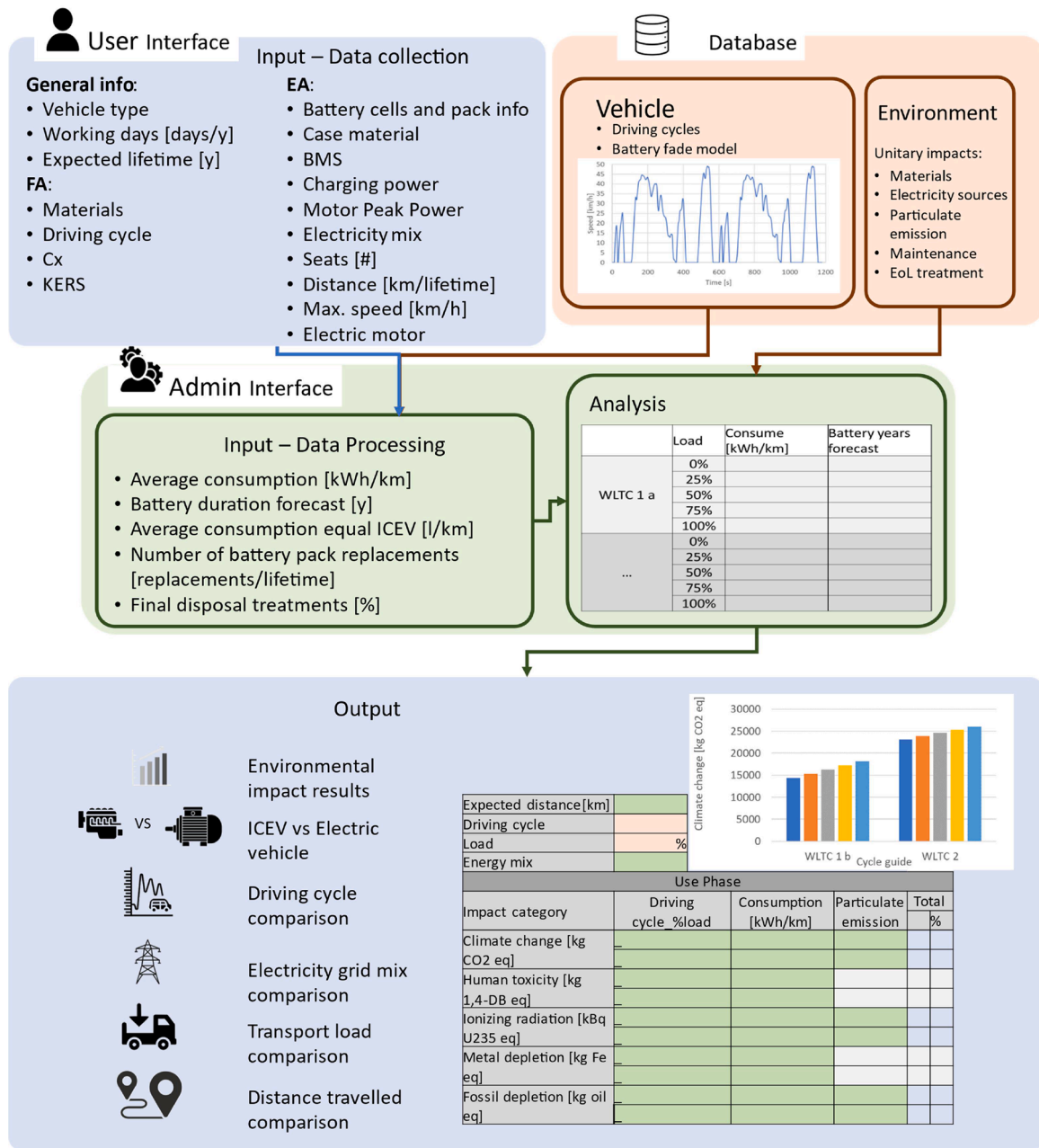


Fig. 2. Tool structure and workflow.

percentage. The use phase gathers the information to calculate the reference electricity grid mix and energy consumption. The first requires the vehicle’s average consumption, which is determined by the tool using the definition of the driving cycle (customized or standard), Cx (coefficient of aerodynamic drag), the vehicle’s front area, transmission efficiency, percentage of energy recoverable during braking/deceleration, function attributed to the use of KERS (Kinetic Energy Recovery System) and charging power.

By applying the kinematic model to the driving cycle, it is possible to compute the following:

- Average vehicle consumption [kWh/km];
- Consumption of a conventional Internal Combustion Engine Vehicle (ICEV): a vehicle with the same specs but a diesel engine for propulsion.

- Estimating the lifespan of a battery pack based on the capacity of a Li-Ion battery pack and so the amount of battery packs that will need to be changed to cover the entire lifecycle.

Both the preferred EoL treatment and the proportion of material supplied to each treatment must be defined for EoL.

3.3. Analysis

This step determines the environmental impacts, calculated according to the unitary impacts derived by the EcoInvent 3 database and calculated in SimaPro 8.0 with the Recipe midpoint (H) method. Five impact categories were chosen to examine the effects of EVs on the environment, human health, and resource consumption for an accurate analysis. By selecting the climate change [kg CO2 eq], human toxicity [kg 1,4-DB eq], ionizing radiation [kBq U235 eq], metal depletion [kg Fe eq], and fossil fuel depletion [kg oil eq] indicators the analysis considers

different damages, still remaining quick and the tool easy to use in the early design phase. According to Petrauskien et al. [19], these impact categories are the most pertinent. Due to its simplicity and easy comprehension of its overall impact, climate change is the most popular environmental indicator used to measure the environmental impact of EVs [50]. Consideration of the effect on human health is made feasible by human toxicity and ionizing radiation; in the case of ionizing radiation, regular considerations of the composition of the electricity grid are involved; depletion of metals and fossil fuels allows for issues regarding the use of resources; in recent years, metal depletion has assumed an increasingly significant role; in the context of ICEVs the second is crucial.

3.4. Output

The major output of the tool is the total environmental impact of the EV expressed for each phase of the product's life cycle as well as the impact for the metrics. In addition, environmental impact comparison about: I) EV and ICEV, specifically a Diesel engine; II) EV recharged with electricity from different electricity grid mixes, i.e. Italian, European, customized; III) transport loads (0 % - 100 %); IV) driving cycles; V) Traveled distances.

4. Results

The present section shows the results obtained by applying the tool to two different industrial electric products at the very early phase of design. The first is an electric shuttle (ES). The vehicle can carry a maximum load of 1920 kg and it has an unladen mass of 5000 kg including both the EA and the chassis assembly. There is no personalized driving cycle for the ES (Fig. 3). To conduct a broad analysis, three World-wide harmonized Light-duty Test Cycle (WLTC) guide cycles were chosen: WLTC class 1, WLTC class 2 v1.4 and WLTC class 2 [51]. The vehicle will be used for shifts of 8 h a day for 5 days a week for 8 years of life, during which there is no provision for the replacement of the battery that will end its life together with the vehicle. It is estimated that the vehicle will be used for 250 days a year. The battery pack is Li-Ion, replaced if it reaches 80 % of its capacity, or at 1500 cycles. The fade model from Wang [31] is chosen. The tool can optimize the curves of the fade model to comply with the design data of the battery pack, which expresses the capacity of the battery pack as a function of the number of cycles. This function, hidden from the user, allows calculating the maximum distance that the vehicle can travel before replacing the

battery pack and therefore the number of necessary battery packs.

A precautionary approach that considers the highest average consumption (WLTC Class 2) and the highest load percentage (100 %) allows identifying the average distance traveled per day, which is 35 km per day or 70,000 km in 8 years. For the EoL phase, 85 % of metals and 50 % of plastics are sent to recycling; specific EoL treatments have been chosen for the components of the EA; what is not treated is sent to landfill.

The second product is an AMR on which a robotic arm was installed. The vehicle is expected to work for 7 years and to travel 4000 km during its lifetime. During this period there is no replacement of the battery pack. In the following, data inserted and elaborated in the tool are presented. The unladen mass of the vehicle is 150 kg. The electronic components include commercial AMR – without battery and motor; this is because the manufacturer bought both the AMR and the robotic arm and is responsible for the design and construction of the remaining structure. The battery pack and the electric motor refer to AMR, as the engines of the robotic arm have already been considered within its mass. The driving cycle for the AMR is personalized and reaches the maximum speed of 5 km/h (Fig. 3).

Table 3 summarizes the input values chosen for the two products. It shows the input required to the user. Suggested values (yellow-filled cells) are average of typical values to use only when not case-specific data are known for the analyzed case.

The preventive lifecycle phases' results for the shuttle and the AMR are shown in Fig. 4 and Fig. 5 respectively. Both pictures contain two sections: section a) shows the contributions from each phase of the lifecycle; following the tool structure, the Material and Manufacturing phase is composed of FA and EAs. Section b) is a composition of the previous.

The most impacting phase for ES and AMR for the Climate Change indicator is the use phase, followed by the material and manufacturing phase.

Table 4 shows the detailed results obtained for the five impact categories. The material and manufacturing phase overcomes the remaining phases is the Human toxicity and metal depletion indicators are considered.

Fig. 6 compares the preventive environmental impacts when the ES is charged with electricity from the national grid, or 50 % derives from Photovoltaic (PV) plant. In the graph, the maintenance phase is also highlighted, although negligible.

Fig. 7 compares the tool results for two different driving cycles and different loads. This effects the use phase, as the total km traveled

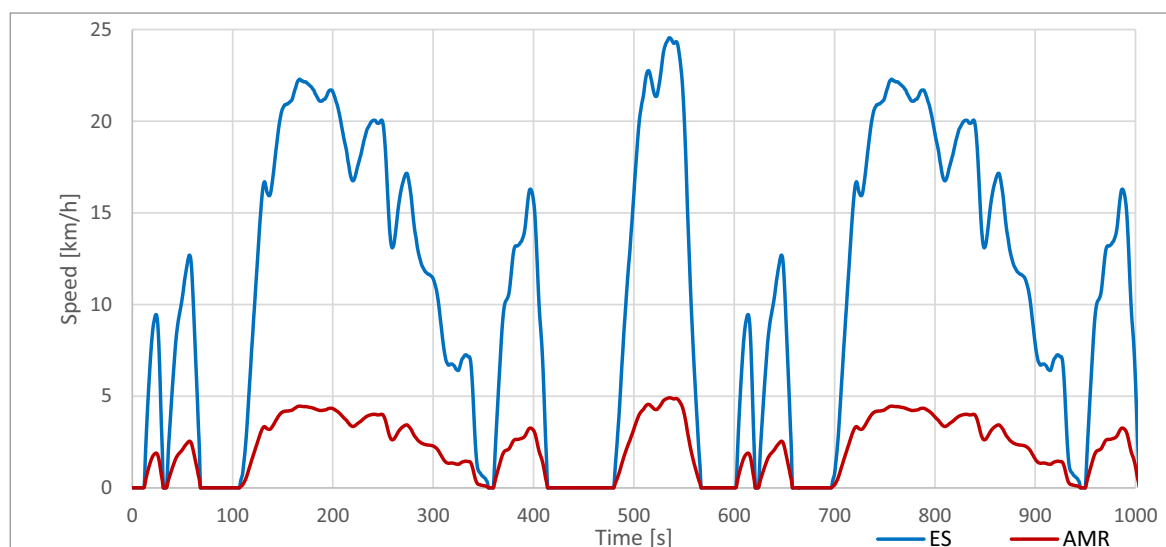


Fig. 3. Driving cycles.

Table 3

Input data on the tool for ES and AMR cases. Suggested values guide the filling of not available information (yellow-filled cells); orange-filled cells require a choice: 1 means guide profile selected; 0 guide profile not selected.

	ES	AMR		ES	AMR
DATA	VALUE	VALUE U.M.	DATA	VALUE	VALUE U.M.
Vehicle type	3	1	ELECTRONIC COMPONENTS		
GENERAL DATA			No. Vehicle control unit	1	0
Daily working hours	8	16 [h/d]	Mass control unit	3,5	0 [kg]
Weekly working days	5	5 [d/w]	No. Charger	1	0
Working years	8	7 [y]	Mass Charger	7,5	0 [kg]
Tot. distance lifetime	20000	4000 [km]	No. Converter	1	0
No. of wheels	4	4	Mass Converter	5	0 [kg]
Max speed	25	4,86	No. Controller	1	0
Area IT	2	2	Mass Controller	16,5	0 [kg]
VEHICLE MODEL			No. Power Distrib. Box	1	0
Contains AGV	0	0	Mass Power Distrib. Box	16,5	0 [kg]
AGV mass		kg	No. Battery 12V	1	0
No. of seats	23	1	Mass Battery 12V	1,5	0 [kg]
Av. person mass	75	0 kg	Massa Cables	10	2,5 [kg]
Av. Passenger load	5	12 kg	Mass Other	5	2,5 [kg]
cx	0,65	0,8	No. robotic arm	0	1
Frontal vehicle area	5	0,2 m^2	Mass robotic arm	0	33,3 [kg]
Battery efficiency	0,98	0,97 EV _{powertrain}	No. commercial AGV	0	1
Efficiency DC/AC Converter	0,95	0,95 0,73	Mass AGV w/o battery and motor	0	32,5 [kg]
Motor efficiency	0,85	0,85	GUIDE PROFILES		
Trasmission efficiency	0,94	0,9	WLTC CLASS 1 a	1	0
Power for auxiliaries	400	50 W	WLTC CLASS 1 b	0	0
KERS	40%	0%	WLTC CLASS 2 v1.4 a	0	0
Charging power	22000	0 W	WLTC CLASS 2 v1.4 b	0	0
Motor Peak Power	90000	10000 W	WLTC CLASS 2	0	0
FRAME ASSEMBLY DATA			WLTC CLASS 3 v5 a	0	0
Empty mass	4500	150 [kg]	WLTC CLASS 3 v5 b	0	0
Steel	60	60 %	WLTC CLASS 3 a	0	0
Wood	2	0 %	WLTC CLASS 3 b	0	0
Plastic	3	15 %	Customized	1	1
Glass	28	5 %	MAINTENANCE		
Fiberglass	2	1 %	Brake changing distance	60000	60000 [km]
Rubber	2	3 %	Tire changing distance	50000	50000 [km]
Aluminum	3	16 %	Electric maint. distance	40000	40000 [km]
BATTERY ASSEMBLY DATA			ENERGY GRID MIX		
BATTERY SYSTEM			Eolic	1,45	1,45 %
Battery (chemical)	1	1	Geothermal/Biomass	0,68	0,68 %
No. of batteries	2	1	Hydro	13,81	13,81 %
Mass (single battery)	130	27,5 [kg]	Carbon/lignite	12,17	12,17 %
Nominal cell capacity	2,9	72 [Ah]	Natural gas	48,12	48,12 %
Nominal cell voltage	3,6	3,2 [V]		8,58	8,58 %
Nominal battery capacity	40,5	72 [Ah]	Nuclear	3,90	3,90 %
Nominal battery voltage	389	32 [V]	Waste-to-energy	0,92	0,92 %
No. of cells (one battery)	1512	10	Solar	8,48	8,48 %
Nominal battery energy	15,78	2,3 [kWh]	Solar_autoproduction	50	50 %
Medium cell capacity 1C	2,75	72 [Ah]	END OF LIFE		
Av. use temperature	25	25 [°C]	% Steel Recycling	85	85 %
% energy @ substitution	80%	80%	% Aluminum Recycling	85	85 %
No. cycles to reach % energy @ substitution	1500	1500	% Fiberglass Recycling	50	50 %
Discharge deep	0,9	0,9	% Glass Recycling	50	50 %
Width	1135	1135 [mm]	% Plastic Recycling	50	50 %
Height	250	250 [mm]	% Rubber Recycling	50	50 %
Depth	449	449 [mm]	% Electric motor treat.	50	50 %
Batthey case thickness	5	1 [mm]	% Electric comp. treat.	50	50 %
Battery case mass	24	5 [kg]	% Battery cell treat.	100	100 %
Battery case material density	2700	2700 [kg/m^3]	% Battery case Recycling	85	85 %
Cell mass	0,048	1,78 [kg]	% Battery BMS treat.	50	50 %
BMS mass	5	1 [kg]	% Battery others treat.	50	50 %
ELECTRIC MOTOR			% AGV treat.	85	85 %
No. electric motor	1	2	% Robotic arm treat.	85	85 %
Mass electric motor	55	1 [kg]			

remain the same, but the consumption changes; for the two shown cases, the unitary consumption per traveled km is 0,234 kWh/km for the customized driving cycle and 0,364 kWh/km for the WLTC class 1a.

Fig. 8 shows a similar graph for the AMR. The customized driving cycle is different from the one chosen in the previous cases.

5. Discussion

The contribution made by the systematic integration of environmental considerations throughout the design life cycle can be very relevant in the initial design phase and have consequences for the subsequent lifecycle phases. The need to allow the environmental sustainability of the product from the early design stages led to the

development of an approach for a simplified environmental assessment. The method is applied in developing a tool to support designers in highlighting the consequences of their choices (from the environmental point of view). Among the main strengths of the tool, its potentiality to be used in the initial design phase when little data are available and quickly receive information relating to the sustainability of the product life cycle.

The tool allows the user to insert customized data (i.e., energy grid mix or driving cycle that carefully describes the traveled paths); impressively, this adds detail to the analysis, but does not hamper the easiness in use. Moreover, the tool successfully addresses and overcomes the problem of scarcity of information; in fact, to carry out a simplified environmental assessment it is provided also with standard data that can

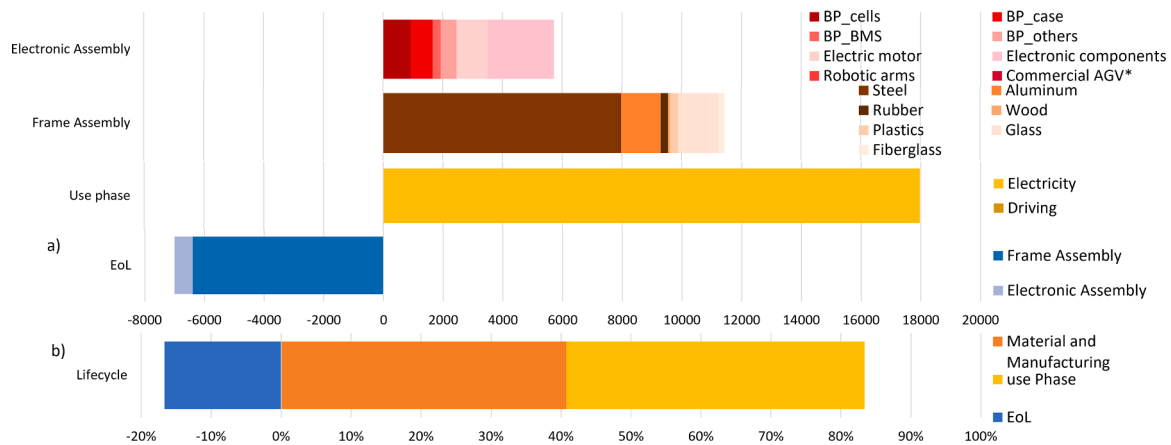


Fig. 4. ES Results per phases (a) and whole lifecycle (b) obtained [kgCo2eq].

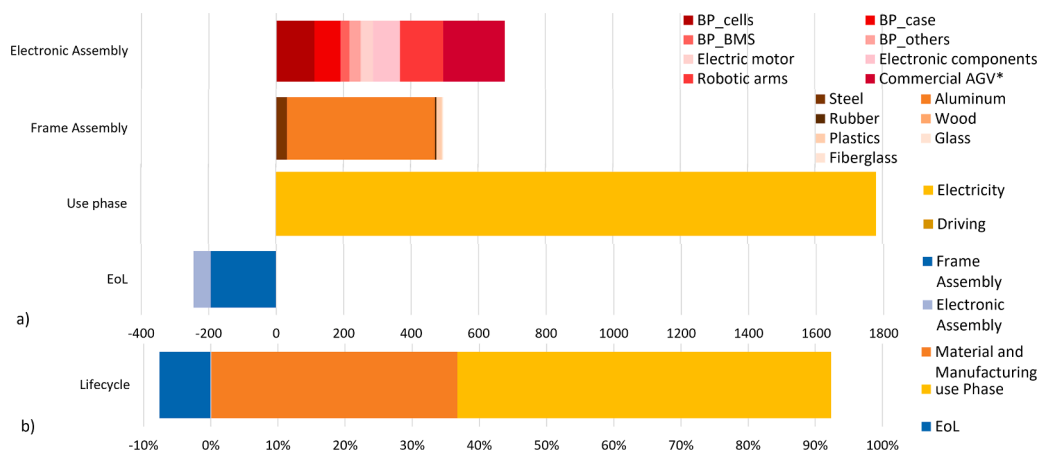


Fig. 5. AMR results per phases (a) and whole lifecycle (b) obtained [kgCo2eq].

be used when any specific information is not available yet for the current case; the user should give priority to the specific data of the use case when available. This avoids obstacles related to off-the-shelf or outsourced components, whose information about processes and materials is inaccurate or absent. With updated information, engineers are able to tightly collaborate on making decisions of parameter selections, which enforces pursuit of global engineering optimization [52].

Although simplified, the preventive environmental assessment considers all the product lifecycle stages. An additional strength lies in the outputs, that are navigable results and thus enable the comparison with different scenarios. The tool can optimize the curves of the fade model to comply with the design data of the battery pack, which expresses the capacity of the battery pack as a function of the number of cycles. This function, hidden from the user, allows calculating the maximum distance that the vehicle can travel before replacing the battery pack and therefore the battery packs necessary during its useful life.

Picatoste et al. [32] analyzed 53 aspects, defined as CE design criteria, then classified by battery life cycle stage (raw materials, manufacturing, transport, use and EoL); the developed tool is based on 4 macro sections of data inputs related to each lifecycle phase and encompasses 108 inputs lines; however, many of them are linked (i.e., WLTC choice, mass percentages and EoL treatments). However, the data insertion is supported by the definition of standard suggested scenarios, that the user can choose if information is not available.

The definition of scenarios is useful to sketch the missing information about the lifecycle phases subsequent the manufacturing, the manufacturing phase of commercial components or environmental information (i.e., percentage of recycling); in fact, the user of the tool may

not be bound to have such knowledge, nor may not be willing or capable to analyze that sort of data [27].

5.1. Results discussion

A precautionary approach that considers the highest average consumption (WLTC Class 2) and the highest load percentage (100 %) allows identifying the average distance traveled per day (35 km per day, equal to 70,000 km in 8 years).

The outputs of the tool provide information of the product lifecycle easily exploitable for the single phases. All the impact categories register a negligible contribution for the EoL; however, the use phase and the material alternatively hold the role of most impacting phase. Comparing the results obtained in this study with those of Petrauskienė et al. [19], the conclusions are the same in terms of phases that have the greatest impact on the specific category. However, it is essential to consider that the study was conducted in Lithuania (different energy mix), on a passenger car (mass 1545 kg, average consumption 0.206 kWh /km) and a total distance traveled equal to 150,000 km. Held et al. [35] argue that for cars, it is the use phase that is the predominant part in the final environmental impact results. These considerations are not in line with the results advocated in this study, as the analyzed products are different. In fact, a car on average has an empty mass of 1500 kg, and an average consumption of 0.150 kWh/km, travelling a total distance of about 200,000 km; instead, the empty mass of the shuttle is more than triple, it consumes about 0.500 kWh/km and is supposed to travel less than half km.

The battery is one of the core components of EVs, its production, use,

Table 4
ES and AMR's results for the five chosen impact categories.

Phase	Sub-phase	Product	Climate change [kg CO2 eq]	Human toxicity [kg 1,4-DB eq]	Ionizing radiation [kBq U235 eq]	Metal depletion [kg Fe eq]	Fossil depletion [kg oil eq]	
Material and Manufacturing	EA	BP_cells	ES	919,22	5710,52	117,17	3650,28	275,66
			AMR	113,33	704,04	14,45	450,03	33,98
		BP_case	ES	739,67	283,56	29,02	22,62	157,92
			AMR	77,05	29,54	3,02	2,36	16,45
		BP_BMS	ES	268,01	1697,89	45,58	325,54	73,89
			AMR	26,80	169,79	4,56	32,55	7,39
		BP_others	ES	536,24	4120,00	81,64	1130,99	158,64
			AMR	33,51	257,50	5,10	70,69	9,91
		Electric motor	ES	1040,82	4626,91	119,54	1322,44	256,84
			AMR	37,85	168,25	4,35	48,09	9,34
		Electronic components	ES	2217,92	11,630,34	353,00	2503,63	577,07
			AMR	79,39	728,51	13,43	168,06	22,91
	Robotic arms	ES	0,00	0,00	0,00	0,00	0,00	
		AMR	128,71	1312,66	17,89	388,80	44,20	
	Commercial AGV*	ES	0,00	0,00	0,00	0,00	0,00	
		AMR	181,92	177,77	15,94	98,59	52,48	
	FA	Steel	ES	7975,83	3872,52	619,85	17,947,49	1749,04
			AMR	32,87	15,96	2,55	73,97	7,21
		Aluminum	ES	1329,37	560,99	58,56	49,18	303,40
			AMR	438,37	184,99	19,31	16,22	100,05
		Rubber	ES	246,73	63,99	40,78	13,74	157,01
			AMR	4,57	1,19	0,76	0,25	2,91
		Wood	ES	73,36	29,40	8,75	4,57	24,73
			AMR	0,00	0,00	0,00	0,00	0,00
Plastics		ES	260,75	28,82	1,98	1,49	134,97	
		AMR	16,12	1,78	0,12	0,09	8,35	
Glass		ES	1348,78	257,99	91,92	269,40	361,00	
		AMR	2,98	0,57	0,20	0,59	0,80	
Fiberglass	ES	209,62	184,28	31,55	15,66	60,83		
	AMR	1,30	1,14	0,19	0,10	0,38		
Use Phase	Electricity	ES	17,947,43	3345,46	1839,73	770,14	5558,25	
		AMR	1780,78	331,94	182,54	76,41	551,50	
	Driving	ES	3,25	10,233,88	0,31	0,18	1,12	
		AMR	0,00	81,23	0,00	0,00	0,00	
EoL	FA	ES	-6391,32	-1744,84	-152,86	-2514,74	-1230,57	
		AMR	-193,99	-62,10	-5,53	-33,25	-41,33	
	EA	ES	-617,71	-196,90	11,70	-1,79	-121,56	
		AMR	-50,59	13,40	2,68	29,95	-10,58	

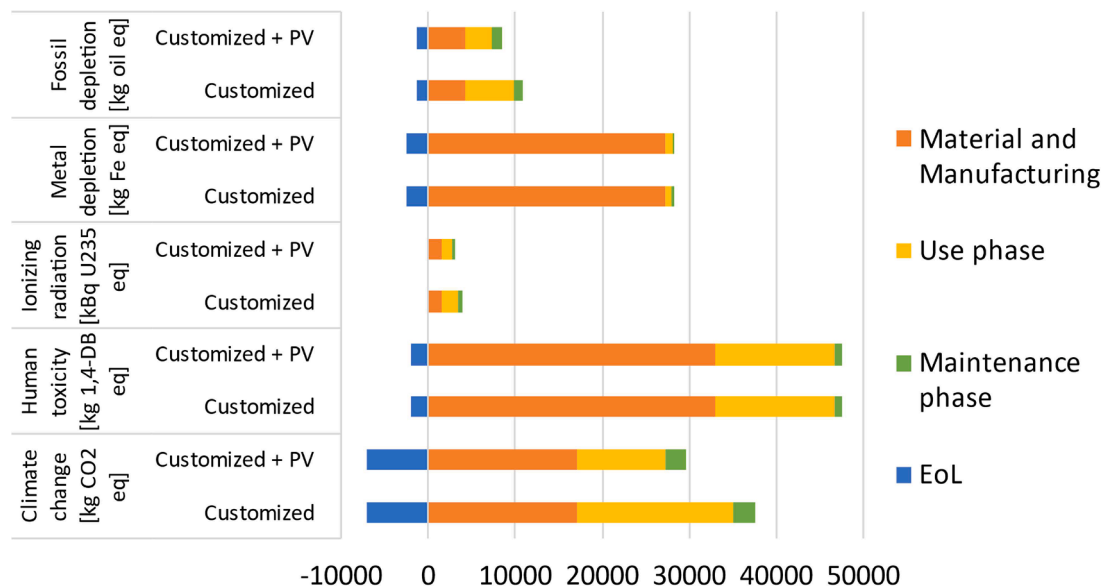


Fig. 6. ES lifecycle impacts, comparison between customized energy mix (energy mix of the company provider) and integration with solar panel.

and disposal have a great impact on the environmental performance of EVs [29]. The obtained results show that this is highly influenced by the nature of the product: the shuttle, that is more massive, sees a consistent

contribution of impacts deriving from the battery pack (kgCo2eq), but the FA retains the main impacts; however, the contribution of impacts deriving from the battery pack increases considerably for other

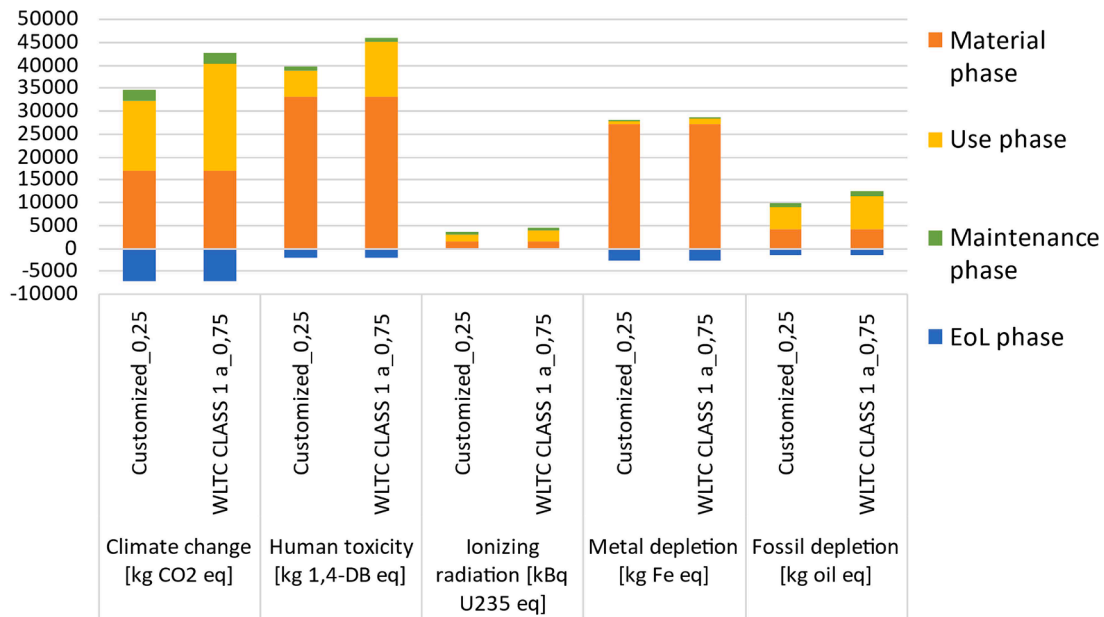


Fig. 7. ES lifecycle impacts, comparison between customized and WLTC Class 1a driving cycles; the first supposes a load of 25 % of full capacity; the latter 75 %.

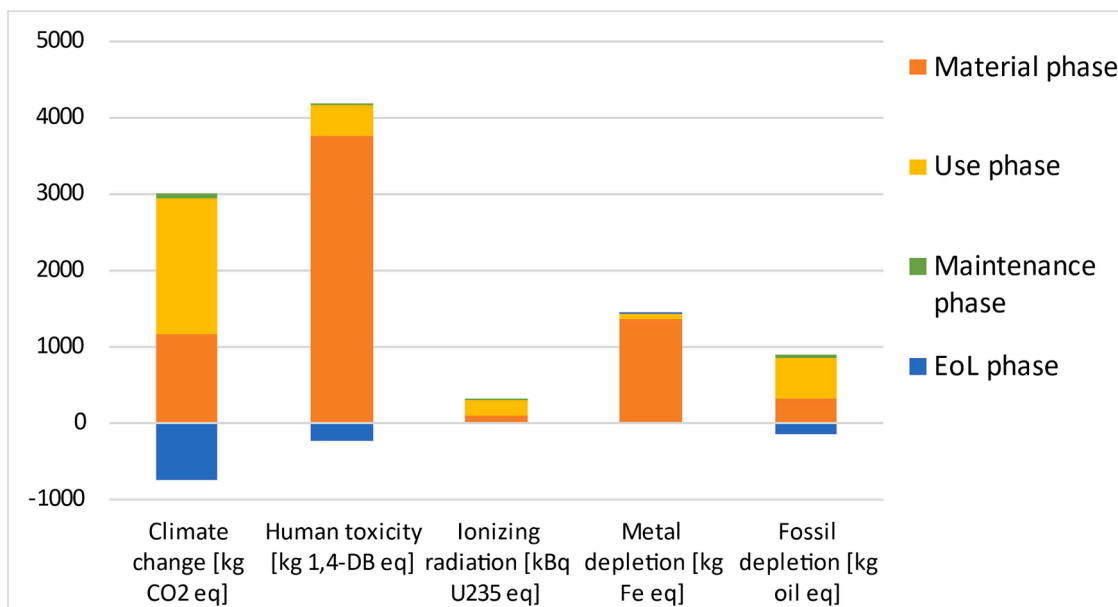


Fig. 8. AMR lifecycle impacts for customized driving cycle with 100 % load.

indicators, as the Human Toxicity. This is due to the level of danger retained by chemicals contained in the battery and used during the production; for example, the cathode active material, the anode substrate and the cell container are hotspots for this indicator [53]. In the specific of the material phase of AMR the EA is the most impactful assembly of the material phase, also because it represents almost 2/3 of the total mass. What can be seen from the graph is that the designer's area of intervention, in this case, is very small because the EA is made up of commercial components, also chosen for technical reasons. Design is a multi-objective process, and the environmental impact is only one of these objectives, which must coexist and be aligned with the others. The aim is in fact to create new opportunities and to reach the optimal solution. The area in which the designer can intervene in the AMR falls on the choice of materials, reducing the masses of steel and aluminum, as far as possible, or increasing the amount of use of aluminum that with

recycling returns an environmental benefit.

Another aspect that the designer can consider is the optimization of the use phase, in addition to the aspects of efficiency and logistics, it is possible to intervene through the supplier on the electricity grid mix. The user can insert customized percentages for the energy mix used to charge the product and can select the percentage of potential auto-produced energy, through PV panels. This highly increases the chances to model different scenarios that better describe the real use case (i. e., the energy mix of the provider of the customer can be inserted, or from foreign countries), as different mixes can lead to widely different impacts [54]. In the case of the ES, considering the climate change indicator, the Italian country mix determines 5 % more kgCo2eq than the mix of the provider; by installing the PV plant, that cover 50 % of overall energy required, the emissions drop of 44 %. The results for the remaining indicators are even more impressive.

5.2. Impacts change as design process evolves

The tool is meant to be used at the very first design phases, when many products details are not defined yet or are subjected to changes. For the two analyzed products, the obtained results are compared with results of an LCA that took as input product data defined at the end of the design process. The comparison aims at assessing the deviation between the LCA shuttle results and those deriving from the predictive analysis. As the trends may vary due to the different hypothesis at the various stages, three types of results are compared: *Tool_start* refers to the data obtained through the predictive tool, at the beginning of the design stage; *Tool_end* refers to the results given by the tool, with the information available at the end of the design stage; *LCA* refers to the detail environmental assessment, done with specific datasets and supported by the software SimaPro, provided with the EcoInvent database.

Therefore, the goal and scope of the three analyses are the same, but with different degree of detail: in the predictive case is lower because it is carried out in a premature phase of the life cycle, prior to the definition of a Bill of Materials (BOM). Fig. 9 and Fig. 10 show the results for the structural components, that are those where the companies designing the ES and the AMR have the most decision power.

Both graphs register a consistent gap between the results obtained with the initial hypothesis and the full LCA. A much lower difference is register between the detailed LCA and the results of the tools, given the ultimate design definitions. The tool is conservative, as only in two cases underestimates the values, if compared to the detailed LCA. However, it gives realistic trends for the same inputs: in the case of ES steel is the material that retains the main impact for the structural part, as registered by the LCA; oppositely, the AMR is mostly made of aluminum, and this is the materials with highest percentage of impacts.

Fig. 9 and Fig. 10 trigger main considerations:

- they prove that the tool is reliable, and it more likely overestimates the impacts, rather than predictive lower impacts; in the cases where it happens (i.e., climate change and human toxicity for AMR), the difference of results is lower than when the results are expected higher than the detailed LCA
- the design phase is subjected to high variability; the going-on hypothesis can radically change; the main consequences are:
 - the *Tool_start* scenario expected much higher environmental impacts; this is due to the initial expectation, according to which the overall mass of the vehicle was 4,5 ton; this value considerably dropped during the design phase

- the simplicity in use of the tool allows to re-iterate the analysis multiple time over the duration of design process, so that the user can rapidly have feedbacks of the new ideas.

Besides the uncertainty, due to a lower level of detailed retained by the tool, the main objective of the tool is reached. Providing hints and feedbacks urges during the during the design phase, rather than obtaining the specific results, that is unobtainable till the end of the design process. In this sense, the method can never substitute for a complete LCA; however, the results can guide in selecting priorities or key strategies.

5.3. Limits and future works

The production phase of the vehicle is not taken into account in the developed tool, i.e., the set of processes that transform the materials into the components then assembled by the vehicle. This limit does not worry about the goodness of the result because in the initial design phase, the definition of all production processes is not yet available in detail. If ever the information related to the chain of production processes is available, is it advisable to evaluate only those that require high energy consumption and therefore have a non-negligible environmental impact. The manufacturing phase was given less priority, as in the literature concerning electric cars, that is the most extended, the most impacting phase of the life cycle is the use phase [35]. Besides the difficulties encountered in evaluating processes and technological processes in the very early stages of design, there is a lack of variability between the different vehicle models in the manufacturing phase [25]. This appears constant; consequently, the designer is unable to intervene. The proposed tool only considers LIBs. Additional types may be added in the structure of the tool, such as LiFePO4 [42] or LiCoO2 [43]. This would also require the introduction of their capacity fade models.

The results obtained from the tool are an approximated evaluation, thus cannot stand as base for certification or disseminating campaigns; however, the tool leads to feedbacks that can further outline optimizations (from the environmental perspective) with low economic impact, as detected and implemented in advance in the lifecycle. However, the results obtained in this study partially differ from those obtained for electric cars, given that in this case, the material phase is the most relevant; in fact, the use phase consider much shorter distances and the structure of the vehicle is much massive (ES) or much lighter (AMR) than passengers cars. For this reason, in the next steps, the manufacturing phase is expected to be introduced within the method by

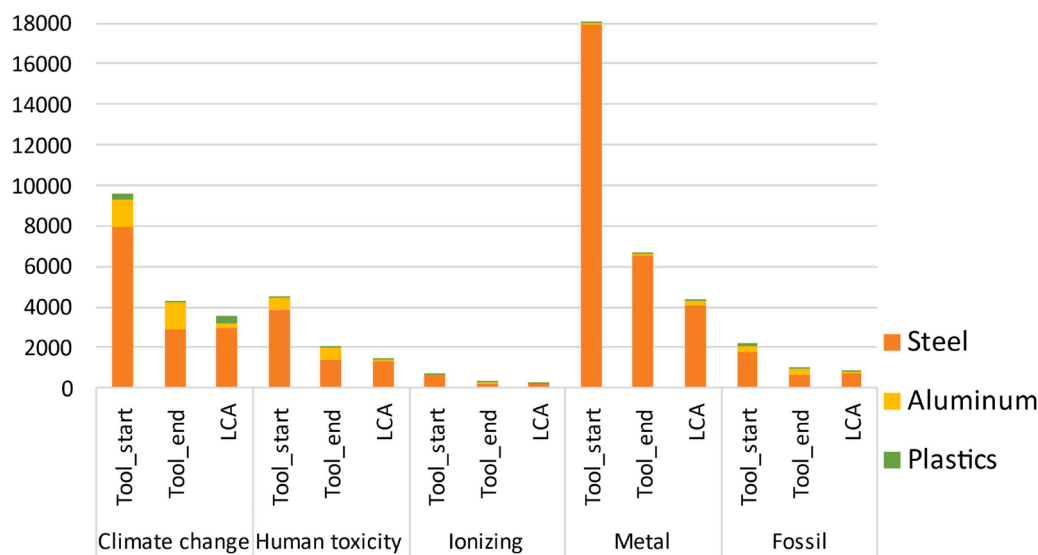


Fig. 9. ES predictive results and final balance.

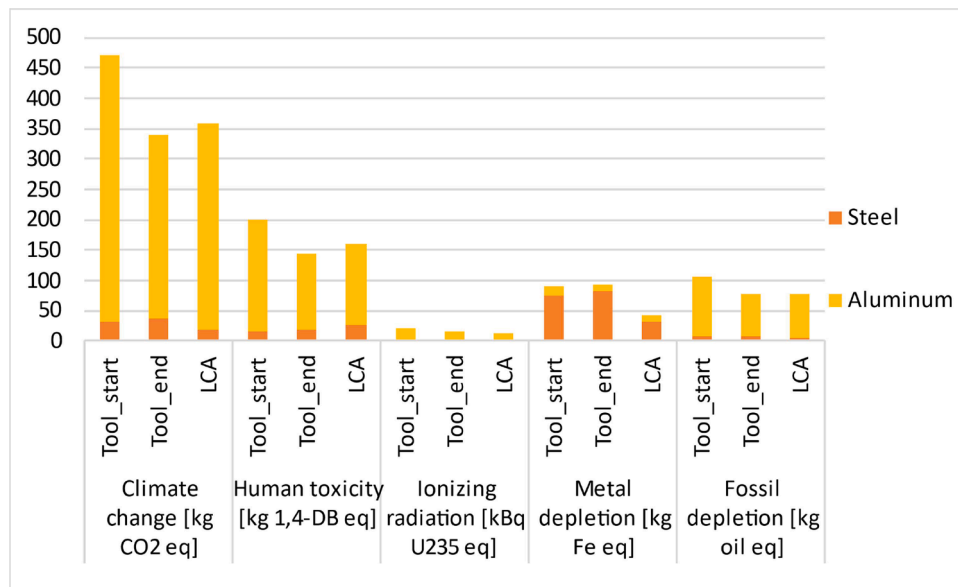


Fig. 10. AMR predictive results and final balance.

parameterizing what are the most important operations. In detail, it will deal with the operations of welding, painting, trimming and assembly, which are the main recurrent in the automotive sector. Furthermore, the study between raw and semi-finished products will be deepened with a differentiation that will also involve the material phase [26].

Machine learning techniques may support future extension of the tool and create parametric models for conceptual and early design; a cluster of the main input parameters of the current tool may be at the basis for the definition of the parameters and databases for training the ML algorithms.

The proposed method and tool can be extended to the economic sphere to obtain a comprehensive picture of the lifecycle, maintaining the same structure. Much of the information required for an economic analysis of the vehicle has already been calculated. Future works may also compare the environmental impacts forecast by the tool with results coming from a full LCA of a certain product. This allows for validating the tool and suggesting further changes for improving it.

6. Conclusion

The requirement to ensure environmental sustainability of the product from the very early design phases has arisen as a result of the rapid technological development that more and more nations are experiencing. A methodology for a streamlined environmental evaluation was created in response to this demand. The authors developed a tool that: i) provides quantitative feedback; ii) converts the WTW analysis into an LCA; iii) is intended for use in the design phase, introducing sustainability concerns in the early stages of the product life cycle; and iv) results are provided for multiple indicators to provide a broad and comprehensive overview. As a result, the authors go beyond the state of the art. The technique has been put into practice as a tool that guides the designer in the decision-making process by evaluating the environmental implications and contrasting various EV life cycle scenarios. The primary goals that guided the creation of the tool and user interfaces were simplicity of use and generating clear findings rapidly. The case studies that allowed for the verification of the proper application in terms of locating the required data. The differences in mass and complexity between the two vehicles under analysis attest to the method's and tool's flexibility. The complete LCA analysis of the two vehicles allowed for the demonstration of how the variability of the final results is primarily dependent on the design data that is available during the initial phase, which are subjected to significant changes. The

potential for growth is huge. For example, the proposed method may be used to anticipate economic impact, and machine learning could be used in a variety of ways to predict environmental damage.

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

Data will be made available on request.

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