Life cycle assessment of shared and private use of automated and electric vehicles on interurban mobility

Mariana Vilaça[a], Gonçalo Santos[b], Mónica S.A. Oliveira[a], Margarida C. Coelho[a], Gonçalo H.A. Correia[c]

[a] University of Aveiro, Centre for Mechanical Technology and Automation, Department of Mechanical Engineering, Campus Universitário de Santiago, 3810-193 Aveiro, Portugal

[b] University of Coimbra, CITTA, Department of Civil Engineering, Rua Luís Reis Santos, 3030-788 Coimbra, Portugal

[c] Delft University of Technology, Faculty of Civil Engineering and Geosciences, Department of Transport & Planning, Stevinweg 1, 2628 CN Delft, the Netherlands

ABSTRACT

The future of road transportation systems faces fundamental changes concerning technological progress and business models. Automated and electric vehicles are coming into the market and evolving towards a service-based mobility system with promises to tackle energy and environmental issues in the mobility sector. Although recent studies have begun to explore the potential impact of shared and privately owned automated and electric vehicles (AEVs) mostly from an operational perspective, little is known about the life cycle impact of such future transport systems. To fill this gap, this paper aims to compare the life cycle environmental impacts of shared vs privately owned AEVs in a regional context. A life cycle assessment (LCA) approach is developed to appraise impact categories with a direct effect on human health, ecosystems, and resources availability. Given that automated vehicles are not yet being used massively, the LCA is applied to synthetic travel demand data to assess the characteristics of privately-owned AEVs and the results of an optimization model that determines the vehicle fleet and driving patterns of shared AEVs serving a regional case-study in the central region of Portugal. Two different vehicle seating capacities - one passenger (non-ridesharing) and four passengers (ridesharing) – are considered to evaluate shared mobility systems. Results show that shared mobility systems yield a potential reduction of up to 42% (with 4 passengers per vehicle) of the system's environmental impacts compared to privately owned automated vehicles. Human toxicity, mineral resource scarcity, and marine and freshwater ecotoxicity are the impact categories with a higher potential of reduction.

KEYWORDS: Automated and electric vehicles (AEVs); Shared mobility; Private vehicle ownership; life cycle assessment (LCA); Flow-based optimization; Intercity

1. INTRODUCTION

The transportation sector is a major contributor to several environmental issues, such as air pollution and global warming. In fact, it is responsible for 24% of direct CO_2 emissions in which road transportation represents nearly 75% of those [1]. Important transformations such as vehicle automation, electrification and shared mobility are expected to affect positively the environmental and health aspects of road transportation [2], [3]. On this base, a scientific and technical rebuttal is rising about the effective sustainability and related consequences of the emerging mobility systems.

In general, the transition from internal combustion engine vehicles (ICEVs) to electric vehicles (EVs) seems to hold widely recognized potential to decrease the amount of greenhouse gas (GHG) emissions by the sector [4]. For instance, based on a normalized vehicle lifetime mileage (150,000 km) the total lifecycle GHG emissions of a medium-size EV can vary in the range between 10 and 52.5 tons while an ICEV varies between 26 and 68.7 tons of CO_2 equivalent [5]. However, the environmental and energy-related performance of EVs strongly depends on the carbon intensity of the electricity mix [6], [7], [8], [9], battery production [10], [11], [12], [13] and disposal [14], [15]. Besides that, at the current level of EVs technological development, it seems that this technology may lead to an increase in the levels of eutrophication, ecotoxicity, and human toxicity when compared to ICEVs mainly due to the production phase [16], [17], [18].

From a life cycle perspective, according to Gawron et al. in [19], adding high levels of vehicle automation features can increase vehicle primary energy use and greenhouse gas (GHG) emissions by 3–20% due to an increase in power consumption, weight, drag, and data transmission. In the same manner, Kemp et al. in [20] reported that vehicle automation features of an SUV or van can increase 2.7% of GHG emissions compared with non-automated EVs. This impact can be offset by operational effects such as eco-driving, platooning, and intersection connectivity that may reduce 9% of the energy use and GHG emissions [19]. From a traffic management point of view, a high level of automated vehicles (AVs) adoption may transform road transportation in several dimensions entailing far-reaching social implications and a consequent, high degree of uncertainty regarding environmental performance. According to the literature, automation can reduce half or increase in double the Greenhouse Gases (GHG) emissions and energy use, predominantly depending on deployment strategies, energy efficiency due to vehicle performance, and consumer behavior [21], [22].

The potential environmental benefits of automated and electric vehicles (AEVs) are reinforced with the promotion of shared mobility [23], [24], [25], [26]. Chen and Kockelman in [27] suggest reductions in energy use and GHG emissions by approximately 51% compared to private-owned vehicles. By replacing 50% of the private cars, a carsharing service is able to reduce 20% of the global warming potential (GWP) of which the distance and number of passengers are crucial factors [28]. The primary concerns related to SAEVs are the limited vehicle range, the configuration of charging infrastructure, and managing the vehicle fleet [29], [30], [31], [32]. Several studies have developed optimization-based models applied to SAEVs to optimally meet urban travel demand considering fleet composition, relocation problems, and parking demand problems [33], [34], [35], [36], [37]. Although most studies have considered SAEVs at an urban scale, vehicle automation is expected to increase long-distance travel because of the decrease in generalized travel costs [38], [39]. Optimization-based models are commonly used to face problems related to routing optimization and fleet sizing in public transport operations where large size networks need to be considered.

Despite the variety of perspectives offered by the previous studies, there is a need for a full understanding of the life cycle environmental burdens of SAEVs considering manufacturing, operation, and end-of-life (EOL), as well as energy supply. It should be highlighted that major research gaps in the existing literature undermine the potential usage of SAEVs. Firstly, most of the previous studies have been considering that SAEVs operate only at an urban level. Secondly, most of the currently available life cycle assessments (LCA) of mobility systems often consider greenhouse gas (GHG) emissions to be the only environmental indicator whereas the available evidence overwhelmingly points to the importance of other pollutants. Future research on LCA of mobility systems should provide a comprehensive overview to support adequate policymaking.

This paper proposes an approach that compares an LCA of SAEVs with an LCA of privately owned AEVs. An optimization model whose objective is to maximize the profit of a company operating in a regional context (intercity trips) is used to design the fleet size and vehicle movements needed to meet the travel demand. The LCA framework of shared and privately owned AEVs is developed considering eighteen midpoint impact categories that cover the three main areas of protection: damage to human health, ecosystems, and resource availability. To the best of the authors' knowledge, this work is the first that presents a full application of LCA to the context of comparing different fleets of AEVs used as private or shared transport. Moreover, part of the innovation of this paper is also related to the regional application of such mobility system, which has been mostly overlooked. Due to the contrast in the socio-economic development of the population and consequent travel modes, private vehicle ownership and passenger behavior, the future trends of inter-city trips will vary significantly when compared to urban mobility. Providing SAEVs at a regional scale could make transport more inclusive, increasing accessibility options for all citizens, especially those that may lack suitable public transport services in low-demand areas but also an effective action for decarbonization of the road transport sector [40], [41].

The results of this study culminate with the application of the proposed framework in the current context of a regional mobility case study. Integrating this capacity to consider different operational scenarios and assess life cycle impacts of different fleet technical options intends to benefit decision-makers and assist vehicle engineers in designing more energy-efficient mobility systems and reduce the overall environmental footprint. The findings of this study also provide to the scientific community the magnitude and comparative weight of the wide range of energy and environmental impacts involved in the deployment of an AEV fleet.

This paper is structured as follows. In section 2, the methodology is proposed emphasizing the mathematical programming model and the lifecycle assessment approach. Section 3 discusses the methodology applied to the regional case study of Aveiro (Portugal). Results from this study are presented in section 4. The paper ends with section 5 which highlights the most important findings and provides directions for future research.

2. METHODOLOGY

This paper proposes a methodology that comprises two main parts: a mathematical programming model and an LCA approach. The mathematical programming model enables to obtain the AEV characteristics that optimally meet the interurban mobility. By adjusting the fleet characteristics to the functional unit of 150,000 km travelled per vehicle over 5 years, an LCA is then applied to compare three established scenarios: privately owned AEVS (scenario S0 – Baseline scenario) and shared mobility scenarios considering a vehicle seat capacity of 1 passenger (scenario S1) and 4 passengers (scenario S2). Fig. 1 shows the generalized framework of such a methodology.

Reference optimized fleet sizes and vehicle movement data serving the regional case study demand for the different scenarios are retrieved from a flow-based optimization approach. This is done for a typical day, however, the optimal fleet size is then estimated for a service period duration (i.e., 5 years) considering that each vehicle in the fleet needs to be renewed according to their lifetime (i.e., 150,000 km). The number of vehicles used during the SAEV service period is divided into two groups: the group of vehicles (number and characteristics) that reaches its lifetime mileage, and the group of vehicles that never reach their lifetime under the period of 5 years which is the time horizon of our analysis. For the last group, a percentage of usage was considered, which is applied to their impacts to produce valid comparisons between scenarios (see Fig. 2).

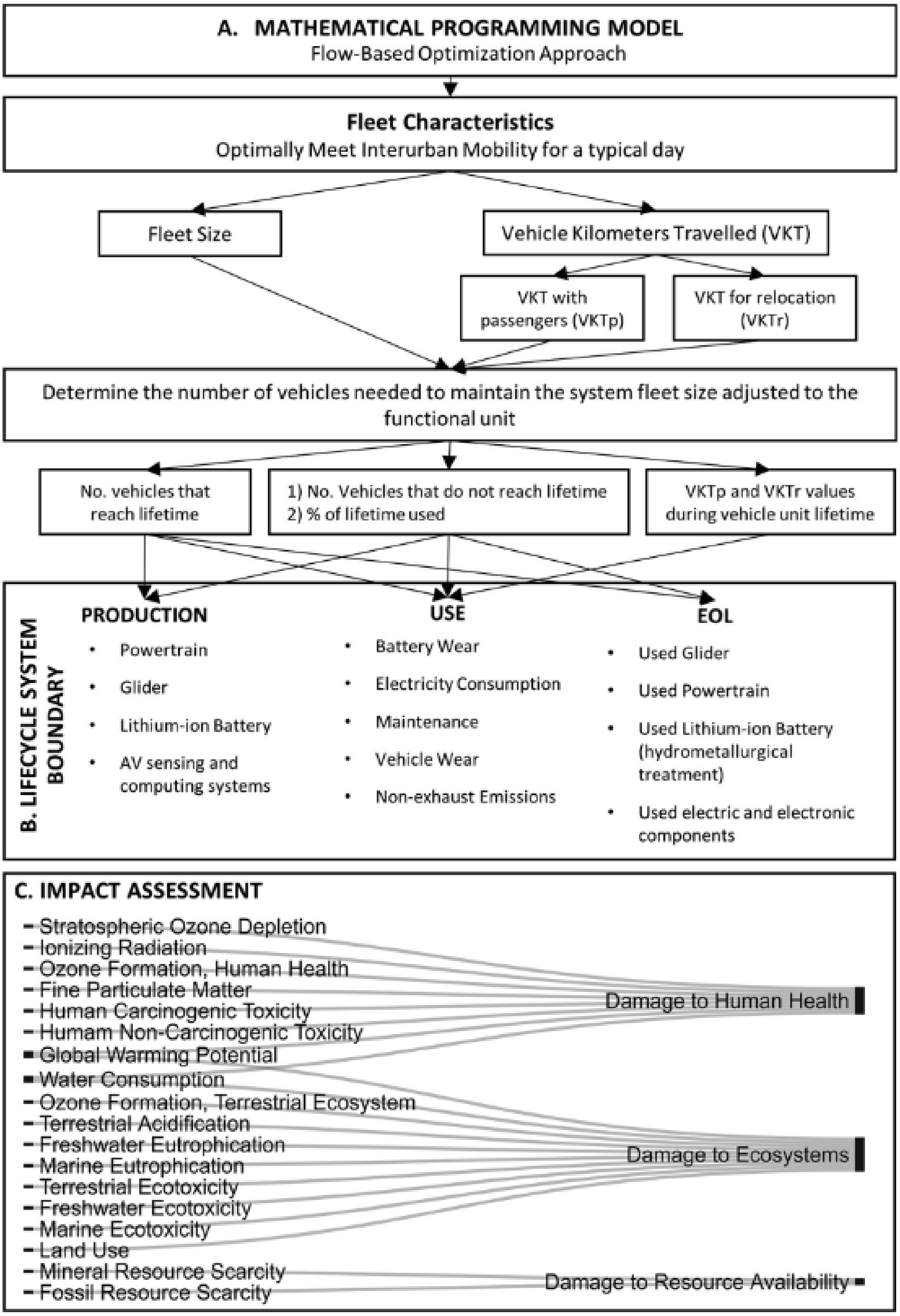

Fig. 1. Methodological framework for the LCA of privately owned and shared AEVs.

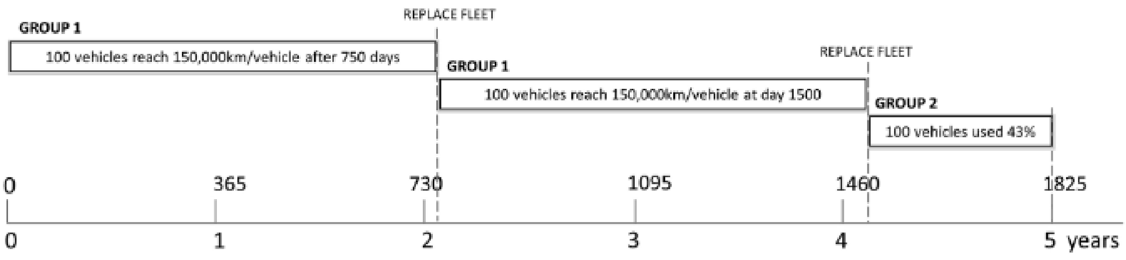

Fig. 2. Groups of vehicles according to their lifetime in the modeled 5 years.

According to Fig. 2, a fleet of 100 vehicles travelling on a daily average of 200 km/vehicle will reach a vehicle lifetime of 150,000 km after 750 days. On a 5-years basis is possible to estimate that 200 vehicles reach their lifetime (Group 1) and the last fleet of 100 vehicles only used 43% of their capacity (Group 2). Fig. 2 is a representative example of the estimation of the two different groups of vehicles. This estimation is made according to the characteristics of each scenario. Moreover, the daily distances traveled, divided by the vehicle kilometers traveled with passengers (VKT_p) and vehicle kilometers traveled for relocation (VKT_r), in the case of shared mobility, are used to calculate the odometer distance and define the vehicle groups. After having the fleet characteristics on the same comparison base, the proposed LCA is performed with a cradle-to-grave approach, comprising production, use, and EOL phases. The number of vehicles used to sustain the optimal fleet size for target service duration (5 years) affects the three life cycle phases, and VKT (divided by VKT_p and VKT_r) directly impacts the use phase. The impact assessment follows the Recipe Midpoint method, evaluating 18 midpoint impact categories (see Fig. 1 and Table 1) with damage to three main areas of protection: human health, ecosystems, and resource availability [42]. The mathematical programming model and LCA are detailed in section 2.1 and section 2.2 respectively.

2.1. Mathematical programming model

Currently, it is not possible to find such a SAEV system in operation in a regional context, hence the need to assess such a system by using mathematical models. To do so, a flow-based optimization approach is proposed to determine the fleet size and optimal vehicle movements of a SAEV system that serves the trip demand between the cities of the region in a day. This approach uses a similar integer programming model to the one proposed by Santos and Correia in [40].

The model considers a region divided into cities ($i \in I$), each city represented by a centroid, and time divided into time instants ($t \in T$). It is built upon a two-dimensional time–space network $I \times T$, where the nodes $n \in N$ represent time–space instances (i, t), and the arcs $a \in A$, with coordinates (i_1, i_2, t_1, t_2), represent three types of flows: the flow of moving SAEVs transporting users (subset $A_u \subset A$) from city i_1 to i_2 ($i1 \neq i2$) starting at time t_1 and finishing at $t_2 = t_1 + u_{i1\ i2}$, being $u_{i1\ i2}$ the travel time to transport users from i_1 to i_2; the flow of vehicle relocations (subset $A_r \subset A$) from city i_1 to i_2 ($i_1 \neq i_2$) starting at time t_1 and finishing at $t_2 = t_1 + r_{i1\ i2}$, being $r_{i1\ i2}$ the travel time to relocate from i_1 to i_2; and the flow of idle vehicles (subset $A_i \subset A$) associated with stopped vehicles at city i from t_1 to t_2 (in this case $i_1 = i_2$).

The demand $d(i, j, s)$, expressed in number of passengers, is characterized by having an origin at city $i \in I$, destination at city $j \in I$, and intended trip start at time instant $s \in T$. Each vehicle has a seating capacity of m passengers. The travel times between origins and destinations are known constants. This is not a limitation in a regional application where intercity trips do not experience significant traffic congestion.

It is assumed that the SAEV system serves all the intercity trips. Users travel directly from the city of origin to the city of destination, meaning that the passengers sharing a vehicle for a certain trip, share the same origin and destination cities. In the case of transporting over one passenger, intra-city movements are performed to pick-up and drop-off the additional passengers. The added time related to the intra-city movements is included in the travel time of arcs $a \in A_u$, the same for the added distance in the arcs' distances. The added time and added distance values of arcs $a \in A_u$, are determined considering the most conservative scenario of a full car, which guarantees that the modeled driving times to pick up (at the origin) or drop-off (at the destination) the passengers are always sufficient for any number of transported passengers. Lastly, the model considers that the adopted technology allows recharging vehicles during their idle time, not affecting the vehicles' movements with passengers or relocation operations.

The decision variables of the problem are the flows expressed in the number of vehicles on each arc, *flow(a)*, and the total number of vehicles composing the fleet, *v*.

The mathematical formulation is:

$$\max(profit) = \sum revenues - \sum costs \quad (1)$$

Subject to:

$$\sum_{a \in A|(i_2=i \wedge t_2=t)} flow\,(a) = \sum_{a \in A|(i_1=i \wedge t_1=t)} flow(a), \forall (i,t) \in N \wedge t > 1 \quad (2)$$

$$d\,(i,j,s) \leq m \times flow(a)_{(a \in A_u|i_1=i \wedge i_2=j \wedge t_1=s)}, \forall i,j \in I \wedge i \neq j, \forall s \in T \quad (3)$$

$$\sum_{a \in A|t_1=1} flow\,(a) = v \quad (4)$$

$$flow(a) \in \mathbb{N} \cup \{0\}, \forall a \in A \quad (5)$$

$$v \in \mathbb{N} \cup \{0\} \quad (6)$$

The objective function (1) maximizes the profit of a SAEV system, being the revenues associated with the price charged per passenger and the costs related to the movement of the vehicles (energy costs), and fixed costs (such as vehicle leasing, insurance, cleaning, and maintenance). Constraint (2) guarantees the conservation of flow at each node of the time–space network. Constraint (3) ensures that the aggregated capacity of vehicle flow serving the considered demand can transport all passengers. Constraint (4) determines the total number of vehicles of the fleet, ensuring that the sum of flows that leave at the first instant is equal to the total number of vehicles in the fleet. Constraints (5) and (6) are related to the variables' domain, ensuring that all variables are non-negative integers.

The integer programming (IP) model output values related to vehicle flows should be post-processed to increase their precision, include a correction for flows with empty seats, and determine the average travel time experienced by passengers.

The model uses time discretized in time instants, and consequently, the output time values are expressed in time step units. To increase the precision of the output values, the original travel times (before transforming them into time steps) were multiplied by the optimal vehicle movement list, an output of the IP model, to compute the final realistic travel times.

The travel times associated with flows are model parameters defined for vehicles moving at full capacity, being the added pick-up and drop-off component of time $t_{adij} = t_{adi} + t_{adj}$ calculated considering a car that fills up all seats. In an optimal flow, the e can be empty seats (less than *m-1*, related to constraint 3), corresponding to a vehicle partially empty that, in reality, experiences a reduction of the modeled travel time because it has fewer passengers. To correct the value of the travel time related to this vehicle moving with empty seats (which has a different impact on the LCA), the added pick-up and drop-off component of time t_{adij} (initially calculated for the most conservative scenario where m seats are fully used) was fractionated according to the number of passengers transported, *k*, and capacity, *m*, using the expression *(k-1)/(m-1)*. Therefore, the travel time for a vehicle traveling between cities *i* and j transporting *k* passengers is given by $t_{intercityij} + (k-1)/(m-1)\ t_{adij}$, form > 1, being $t_{intercityij}$ the travel time between cities *i* and *j* without considering the added time to pick-up and drop-off extra passengers. If $m = 1$, this correction is not needed since a vehicle can only carry one passenger (not having additional time to pick-up and drop-off extra passengers). A similar process was used for the vehicle movement distances.

Different passengers, sharing the same vehicle, experience different travel times. To transform optimal vehicle flows into passenger travel time, the average travel time experienced by each passenger in a vehicle was estimated using proportional weights applied to the pick-up and drop-off travel time component, t_{adij}. The weight of each passenger, *p*, traveling inside a vehicle follows an arithmetic progression with p^{th} term equal to $(p-1)/(m-1)$, being $p \leq m$. Using the sum of this progression, the aggregated passenger travel time experienced by k passengers transported in a vehicle, with capacity *m*, between cities *i* and *j* is equal to $k \times t_{intercityij} + k(k-1)/(2(m-1))$, t_{adij} . If $m = 1$, this correction is not needed.

The optimal results obtained from this model, namely fleet size and vehicle distance traveled (VKT_p and VKT_r) are used as an input of the LCA. Different characteristics of fleet vehicles, namely seat capacity and battery type, can be used to formulate scenarios since it directly affects the life cycle phases (production, use, and EOL).

2.2. Life cycle assessment

An attributional LCA is developed to assess the impacts of shared and privately owned AEVs applied to a regional demand context. The methodology described encompasses the production, use, and EOL life cycle phases. The LCA framework is described in three steps following the international standards [43]. The first is the definition of goal and scope which include the setting of the functional unit and reference flow. The second step describes the system boundary covered in this study. The third and last step characterizes the impact assessment approach and impact categories evaluated.

2.2.1. Goal and scope

The goal is to estimate the life cycle impacts of a fleet deployment of optimized privately owned and shared AEVs in a regional context. The scope includes a comparative analysis between privately owned AEVs (scenario S0) and two alternative scenarios of shared AEVs based on vehicle seat capacity: one passenger (scenario S1) and four passengers (scenario S2).

The functional unit of this study is an AEV fleet with a service life of 150,000 km per vehicle (assumed as the useful driving distance of vehicles in corporate fleet operations [44]), developed to optimally meet the total of the current travel demand of the regional case study, over 5-years timeframe. The flow-based optimization model used to estimate the number and vehicle characteristics composing the fleet aims to maximize the profit considering that the mobility service is operated by a company. The 5-years scenario timeframe was chosen to include multiple fleet replacements and to provide a comparison basis.

2.2.2. System boundary

The system boundary covers the life cycle phases of vehicle production, use, and EOL and the impacts related to the production and use of the energy needed to operate the vehicle under intercity trips. On the production phase, the AEV is an assembly divided into four main sub-assemblies: the glider, which represents the vehicle body and chassis; the powertrain, compounded by the electric motor, charger, inverter, power distribution unit and converter; lithium-ion battery package; the sensors and computing systems (See Fig. 1). The Ecoinvent database (version 3.7.1) was used as a background inventory database [45]. Individual component characteristics of sensing and computing subsystems that equip the level 4 AVs were obtained based on [19] and the material composition selection based on the authors' technical knowledge of the materials.

The use phase accounts for energy consumption, maintenance, vehicle and battery wear, and non-exhausted emissions (brake, tire, and road wear). This process is parameterized in terms of vehicle and battery mass, energy consumption, and vehicle and battery lifetime (expressed in kilometers). Moreover, the direct effects of sensing and computing subsystems, and the direct effect of vehicle automation such as eco-driving, platooning and intersection connectivity was considered based on existing data [19]. Indirect mobility level effects such as vehicle kilometers of relocation, high-intensity utilization due to carsharing are taken into consideration. SAEVs potential effects such as lightweight, rightsizing, higher travel demand, and congestion mitigation are out of the study scope.

The end-of-life phase consists of vehicle dismantling and recovery of the main plastic and ferrous-metal components. Regarding the lithium-ion battery treatment, a hydrometallurgical process consisting of metals extracted at low temperatures was considered [46]. Electronic components (sensing and computing systems devices) require manual dismantling and mechanical treatment. This phase is modeled considering the cut-off approach, which means that the environmental burdens of recycled materials are not accounted for the impacts of the disposed products, but to the next product generation. The main processes and materials involved in the life cycle inventory are listed in supplementary material - S.M.1.

2.2.3. Impact assessment

The LCA is carried out using SimaPro LCA software package (version 9.2), a widely used LCA tool. The impact assessment is developed based on ReCiPe midpoint method, considering a hierarchical perspective [42]. Table 1 describes the environmental impact categories included in the evaluation. The impact assessment relies on commonly established midpoint impact categories instead of more aggregated endpoints.

In total, 18 midpoint impact categories were evaluated with impact to the three main areas of protection: human health, damage to ecosystems, and resource availability (see Fig. 1).

3. APPLICATION OF THE METHODOLOGY TO THE AVEIRO REGION IN PORTUGAL

The proposed methodology is applied to the Region of Aveiro, Portugal, composed of 11 municipalities with 1,693 Km2 and 370 thousand inhabitants- Fig. 3 [47]. Each municipality has between 95 and 525 inhabitants per square kilometer.

This study analyses the intermunicipal trips between the municipalities in the region, a total of 118 thousand trips per day [47]. For the current application, the municipalities of Aveiro, represented by its centroids, correspond to the cities of the mathematical programming model. The aggregated data from the Intercity Report of Aveiro Region (IRAR) - [47] was used to generate the synthetic travel demand, a consequence of not having access to the raw data. A Poisson process was used to generate the trip demand which respects the OD matrix values and the hourly trip distribution for the entire region. To increase the realm of the synthetized values, the disaggregation of the hourly trip distribution for each municipality was made. This disaggregation had, as structural references, some municipalities selected from a neighbour region for which raw trip data is available. The selected municipalities share similar characteristics with the ones of the Aveiro region, particularly the number of daily trips and distance to the most important municipality of the region. The Furness method [48] was used to guarantee that the border conditions from the IRAR (total trips per hour, and daily total trips per municipality) are simultaneously respected.

Table 1
Impact Categories evaluated [42]

Impact Category	Unit	Description
Global Warming Potential (GWP)	kg CO_2 to air	GWP establishes the amount of greenhouse gases produced with a direct or indirect effect on global warming.
Stratospheric Ozone Depletion	Kg CFC-11 to air	Applies to emissions of ozone depletion substances, namely trichlorofluoromethane (CFC-11), ultimately leads to damage to human health because of the resultant increase in UVB-radiation.
Ionizing Radiation	kBq Co-60 to air	It reflects the anthropogenic emission of radionuclide in the environment, particularly associated with electricity generation from both coal and nuclear power. Exposure to ionizing radiation can lead to damage to DNA-molecules with a direct impact on human health.
Ozone Formation, Human Health	kg NOx to air	Ozone formation results from photochemical reactions of NOx and non-volatile organic compounds (NMVOCs). This has a particular impact on human health but also on vegetation, namely reduction of growth and seed production, an acceleration of leaf senescence, and a reduced ability to withstand stressors.
Ozone Formation, Terrestrial Ecosystems	kg NOx to air	
Fine Particulate Matter Formation	kg PM2.5 to air	Suspended particular matter corresponds to less than 2.5 μm in diameter (PM2.5) particles suspended in the atmosphere, which results in chemical reactions leading to aerosols of sulfur oxides, nitrogen, and ammonia.
Terrestrial Acidification	kg SO_2 to air	Terrestrial acidification accounts for the gases of ammonia (NH_3), nitrogen oxides (NO_x), and sulfur oxides (SO_x). This impact category is directly related to damage to ecosystems.
Freshwater Eutrophication	kg P to freshwater	Eutrophication is related to the discharge of nutrients into freshwater and the consequent rise in nutrient concentration, particularly phosphorus and nitrogen. These impact categories have a particular effect on ecosystems, namely damage to freshwater and marine species.
Marine Eutrophication	kg N to marine water	
Terrestrial Ecotoxicity	kg 1.4-DCB to industrial soil	The toxicity potential is expressed in kg of 1.4-dichlorobenzene-equivalents (1.4-DCB) and is the characterization factor of human toxicity and ecotoxicity. The reference chemical's potential impact is evaluated at urban air for human toxicity, freshwater for freshwater ecotoxicity, seawater for marine ecotoxicity, and industrial soil for terrestrial ecotoxicity.
Freshwater Ecotoxicity	kg 1.4-DCB to freshwater	
Marine Ecotoxicity	kg 1.4-DCB to marine water	
Human Carcinogenic Toxicity	kg 1.4-DCB to urban air	
Human Non-Carcinogenic Toxicity	kg 1.4-DCB to urban air	
Land Use	m^2 annual cropland	The land use impact is related to the disqualification of land as suitable habitat for species and soil disturbance.
Mineral Resource Scarcity	kg Cu	The primary extraction of a mineral resource will lead to an overall decrease in ore grade, which will increase the ore produced per kilogram of mineral extracted. This impact category has a direct impact on the increase of extraction costs and damage the resources' availability.
Fossil Resource Scarcity	kg oil	The ratio between the energy content of fossil resources under evaluation and the crude oil's energy content. The impact category directly affects oil, gas, or coal energy cost and damage the resources' availability.
Water Consumption	m^3 water consumed	This impact category is related to an increase in malnutrition and damage on freshwater species due to the reduction of the watershed of origin availability for both humans and ecosystems.

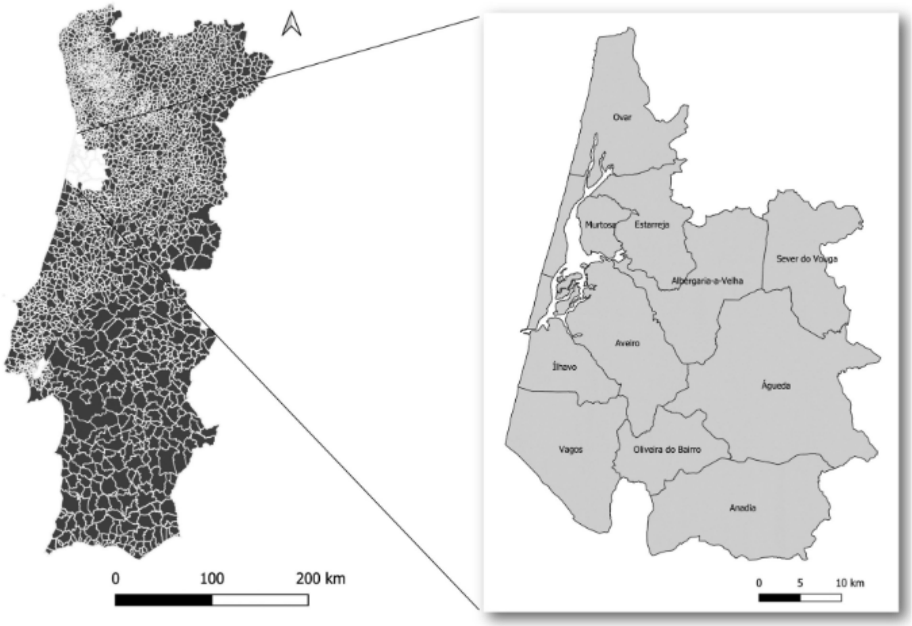

Fig. 3. Geographic location of the Aveiro region case-study in Portugal.

To apply the mathematical programming model, the distances and travel times were obtained from Google Maps [49]. It is assumed that travel times are constant throughout the day. Considering the scenario of the privately owned vehicle, all the intermunicipal trips are considered commuting trips performed by car in which the occupancy rate is 1.2 passengers [50]. Regarding shared mobility services, the added time and added distance to pick-up and drop-off passengers were obtained using an intra-municipality simulation on each municipality $i \in I$. To perform this simulation, the parishes of each municipality have been represented by centroids. Requests were generated for each parish of a certain municipality using the inverse transform sampling method applied to the population ratio of each parish in the municipality population. The number of generated requests is equal to the vehicle capacity (a condition assumed in the model description). The shortest distance between requests is determined using a simulated annealing algorithm. This simulation is repeated one hundred times for each municipality, being the average used to process the added time, as well as the added distance for the referred arcs.

The cost coefficients of the mathematical programming model are set as follows. The driving cost, associated with vehicles' movements, considers the kWh price in Portugal, which is approximately 0.20€ [51]. The vehicle's daily cost, a fixed expense per vehicle, includes the daily depreciation value based on the 20% depreciation rate per year [52], and the daily cost of maintenance, taxes, insurance, and cleaning. The service price charged to passengers is the only source of revenue considered for shared mobility systems. The adopted price is 0.10 €/km for the service with polling (a maximum of 4 passengers per vehicle), and 0.15€/km for the service without pooling (one passenger per vehicle). The service price charged to passengers (revenue) minus running costs (particularly related to vehicle movements) and vehicle daily costs (depreciation, maintenance, taxes, insurance, and cleaning), reflect the company profit.

The fleet consists of compact-size passenger vehicles similar to Renault Zoe, 1845 kg of curb weight, 52kWh battery capacity, 150,000 km of battery lifetime and 20kWh/100 km energy consumption [45], [53], [54]. The characteristics of the compact-size passenger vehicles are considered the same for all the scenarios. Sensing and computing features were assumed to increase raw materials consumption, vehicle weight by 16.5 kg and vehicle power consumption by 2%. Life cycle inventory data is displayed at supplementary material – S.M.1.

The LCA is modeled considering an average vehicle for scenario S0. At scenarios S1 and S2 two different average vehicles are considered: one that reaches the lifespan and another one that does not reach it respectively. The production and EOL phase are mainly influenced by the number of AEVs comprising the fleet. Different scenarios of vehicle occupancy influence particularly the size of the fleet as well as the VKT_p and VKT_r during the use phase. For the VKT_p the extra weight of passengers for all scenarios is considered. For that purpose, the average weight of 60 kg per passenger is assumed [55]. The AEVs energy consumption during the use phase is modeled based on the Portuguese electricity generation mix (data from 2014) which is supplied by 31.8% hydro, 23.4% wind, 23.1% coal, 13.2% natural gas, 5.4% biofuels, 2.6% oil, and 0.5% geothermal power [56].

4. RESULTS

4.1. Mathematical programming model

Table 2 presents the optimal results of the mathematical programming model considering the demand of the regional case study for scenario S0: private AEVs with an average occupancy rate of 1.2 passengers; scenario S1: SAEVs with an occupancy rate of 1 passenger (non-ridesharing) and scenario S2: SAEVs with an average occupancy rate of 3.0 passengers per vehicle (ridesharing).

Table 2
Optimal daily fleet characteristics and accounting profit under scenarios S0, S1 and S2.

	Units	Scenario S0	Scenario S1	Scenario S2
Fleet composition	#vehicles	49,857	9,311	3,393
VKTp	km/day	35.6	223.7	504.1[A]
VKTr	km/day	0	27.2	12.8
Vehicle average occupancy rate	#passengers	1.2	1	3.0
Average travel time per passenger	Minutes	21	21	36
Cost fleet moving with passengers	€/day	70,927	83,327	68,410
Cost fleet relocating	€/day	0	10,137	1,735
Cost fleet composition	€/day	997,140	186,220	67,860
Revenue	€/day	0	313,233	208,822
Profit	€/day	−1,068,067	33,549	70,817

[A] 67% to pick-up and drop-off.

Scenario S0 is the baseline scenario and intends to reflect the optimized characteristics of the actual fleet operating in the Aveiro region. To optimally meet the travel demand, 49,857 privately owned vehicles are needed, traveling an average of 35.6 km/day. The scenarios of shared mobility (S1 and S2) indicate a reduction of 81% and 93% of the fleet size, respectively. The reduction in terms of the number of vehicles is offset by a high vehicle-use intensity. Compared with scenario S0 (baseline), vehicles traveled in average 6 times and 12 times more kilometers per day on scenario S1 and scenario S2, respectively.

Considering the weight of costs in the representative system scenarios, the cost of the fleet composition is the most important. Profit wise, scenario S0 where no revenue is considered, the use of privately owned vehicles represents an aggregated cumulative loss of around one million euros per day. In contrast SAEVs systems, replacing the same passenger movements, under scenarios S1 and S2 have a profit of 33,549€ and 70,817€ per day, respectively. From a user perspective, the increase of 15 min' travel time per passenger in scenario S2 when compared to scenarios S0 and S1 is an indicator of the reduction of service quality.

The previous optimization results consider a typical day of operations, though vehicles need to be replaced after each vehicle reaches the lifetime (150,000 km). A 5 years-period of analysis to verify the impacts of maintaining the optimal daily fleet size was used. At the end of this period, there will be some vehicles that do not reach the lifetime. For those, the relative value of the impacts was considered by applying the percentage value of lifetime used (rate of the mileage used relatively to the total mileage to reach the lifetime). Table 3 reflects these results used as input to the life cycle assessment (Section 4.2).

Table 3
Fleet characteristics adjusted to the functional unit defined per vehicle: 150,000 km/5years.

	Units	S0	S1	S2
Fleet composition	#vehicles	49,857	27,933	23,751
VKTp	%	100	89	98
VKTr	%	0	11	2
Vehicles A: reach lifetime	#vehicles	0	18,715 (67%)	20,426 (86%)
Vehicles B: do not reach the lifetime	#vehicles	49,857 (100%)	9,218 (33%)	3,325 (14%)
Use of vehicles B	%	43	72	13

When considering a lifetime of 150,000 km per vehicle unit over 5 years, the differences between fleet composition under the three scenarios are reduced since it provides the normalization between vehicle-use intensity and vehicle lifespan. When compared to the baseline scenario S0, the total number of vehicles needed to guarantee the necessary fleet size during the 5-year period of analysis reduced 44% and 52% for scenarios S1 and S2, respectively.

4.2. Life cycle assessment

Table 4 reports the results of the impact assessment of each scenario under evaluation. According to these results, shared mobility discloses a potential to reduce 20–31% of the impacts when non-ridesharing is considered – scenario S1 and 32–42% when ridesharing is considered – Scenario S2. The impact categories with the most reduction potential are human toxicity, mineral resource scarcity, and marine and freshwater ecotoxicity, mainly influenced by the production phase and the wear of the vehicle (use phase). Comparing the two scenarios of shared mobility vehicle capacity, scenario S2 can reduce the value of the impact categories by 14–16% compared with scenario S1. Indeed, the better lifecycle performance of scenario S2 is closely related to the reduction of the number of vehicles composing the fleet (Table 3).

Table 4
Impact Assessment of case study mobility under scenarios S0, S1, and S2 (decrease rate compared to the baseline scenario S0**** means a bigger decrease on the impact categories per scenario).

Impact Categories	Name code	Units	S0	S1		S2	
Global Warming Potential	GWP	kg CO_2 eq.	1.84×10^9	1.46×10^9	(−21%)*	1.24×10^9	(−33%)*
Stratospheric Ozone Depletion	SOD	kg CFC11 eq.	8.49×10^2	6.54×10^2	(−23%)*	5.55×10^2	(−35%)**
Ionizing Radiation	IR	kBq Co-60 eq.	1.25×10^8	9.57×10^7	(−24%)**	8.12×10^7	(−35%)**
Ozone Formation, Human health	OF_HH	kg NOx eq.	5.77×10^6	4.58×10^6	(−21%)*	3.87×10^6	(−33%)*
Fine Particulate Matter Formation	PM	kg PM2.5 eq	3.98×10^6	3.08×10^6	(−23%)*	2.61×10^6	(−35%)**
Ozone Formation, Terrestrial Ecosystems	OF_TE	kg NOx eq.	6.14×10^6	4.94×10^6	(−20%)*	4.17×10^6	(−32%)*
Terrestrial Acidification	TA	kg SO_2 eq.	8.29×10^6	6.60×10^6	(−20%)*	5.57×10^6	(−33%)*
Freshwater Eutrophication	FEutro	kg P eq.	1.67×10^6	1.19×10^6	(−29%)***	1.01×10^6	(−39%)***
Marine Eutrophication	MEutro	kg N. eq.	2.14×10^5	1.54×10^5	(−28%)***	1.32×10^5	(−39%)***
Terrestrial Ecoto × icity	TEco	kg 1.4-DCB	9.70×10^9	7.24×10^9	(−25%)**	6.18×10^9	(−36%)**
Freshwater Ecoto × icity	FEco	kg 1.4-DCB	9.22×10^8	6.41×10^8	(−31%)****	5.46×10^8	(−41%)****
Marine Ecoto × icity	MEco	kg 1.4-DCB	1.18×10^9	8.17×10^8	(−31%)****	6.96×10^8	(−41%)****
Human Carcinogenic To × icity	HCT	kg 1.4-DCB	7.31×10^8	5.33×10^8	(−27%)***	4.58×10^8	(−37%)***
Human Non-Carcinogenic To × icity	HnCT	kg 1.4-DCB	1.16×10^{10}	7.98×10^9	(−31%)****	6.79×10^9	(−42%)****
Land Use	LU	m^2a crop eq.	6.58×10^7	4.84×10^7	(−26%)**	4.11×10^7	(−38%)***
Mineral Resource Scarcity	MRS	kg Cu eq.	5.77×10^7	3.96×10^7	(−31%)****	3.38×10^7	(−41%)****
Fossil Resource Scarcity	FRS	kg oil eq.	4.84×10^8	3.88×10^8	(−20%)*	3.28×10^8	(−32%)*
Water Consumption	WC	m^3	1.80×10^7	1.35×10^7	(−25%)**	1.15×10^7	(−36%)**

The production and use are the life cycle phases with the highest contributions to the impact categories, being the impact of EOL almost negligible. Moreover, the relative impact of each life cycle phase is roughly the same when considering a non-ridesharing (S1) or a ridesharing (S2) shared mobility system. As mentioned before, the total reduction of impact categories between the two scenarios of shared mobility is closely related to fleet composition. Fig. 4 shows the relative percentage of each impact category to life cycle phases. The relative percentages reflect the contributions of the three life cycle phases to each impact category.

The production phase accounts for 59 to 79% of the impact categories in scenario S0 and around 41% to 65% in the shared mobility scenarios (S1 and S2). The production phase is the higher contributor to the impact categories such as mineral resource scarcity (79% for scenario S0 and around 64% for scenarios S1 and S2) and human non-carcinogenic toxicity (78% for scenario S0 and around 63% for scenarios S1 and S2). An in-depth look at the process contribution can reveal that the production of the lithium-ion battery and powertrain are the main responsible for these impacts. This contribution is mainly related to the metals and chemicals used in the production of powertrains and high voltage batteries. Results related to the process contribution are in line with data reported on supplementary material (S.M.2).

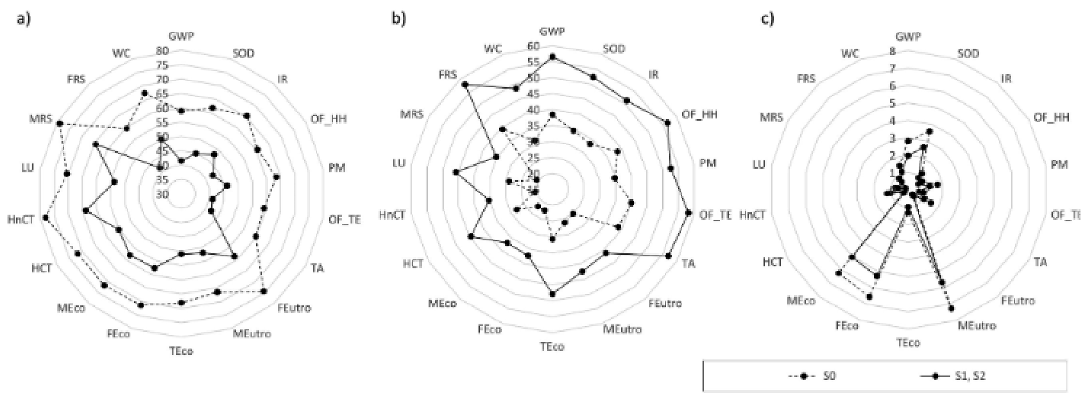

Fig. 4. Relative comparison (%) of the environmental impacts on life cycle phases (a) Production phase; b) Use phase; c) EOL for scenario S0, scenario S1 and S2.

Although the production phase is the life cycle phase with the highest impact in scenario S0 for all the impact categories, the same does not happen in shared mobility scenarios. For scenarios S1 and S2 the use phase represents 35% to 58% of the impact categories while in the baseline scenario is responsible for at most 40%. Because of the high-intensity use of the vehicle, the use phase is a larger contributor for 8 out of the 18 impact categories for scenarios S1 and S2. At the use phase, emphasis is given to impact categories such as ozone formation (terrestrial ecosystems and human health), terrestrial acidification, and fossil resource scarcity. Most of the impacts at the use stage are particularly related to electricity consumption and vehicle wear (supplementary material S.M.2). The end-of-life phase (EOL) accounts only for a maximum of 7% of the impact categories for the three scenarios. At this phase is noticed that impact categories related to the hydric resources damage such as marine eutrophication, freshwater, and marine ecotoxicity are the most relevant.

4.3. Sensitivity analysis

A sensitivity analysis of three key parameters involved in the AEVs LCA was performed to better understand their impacts. The variables for the analysis were selected based on uncertainty and variability. The first parameter is the electrical grid carbon intensity. Considering the massive impact of electricity consumption during the use phase, different electricity generation conditions were tested besides the country mix (PT): electricity generation only from coal, wind, and photovoltaic power systems. Compared with the country electricity mix (PT) an electricity generation based on coal can significantly increase the value of 10 out of the 18 impact categories considered. In contrast, impact categories such as ionizing radiation, ecotoxicity, land use, mineral resource scarcity, and water consumption can benefit from this change. These impact reductions can be explained by geothermal energy (particularly related to emissions of ionizing radiation) and natural gas power (particularly associated with impacts on ecotoxicity) both present in the electricity country mix [57]. Furthermore, electricity generation based on coal energy source is the primary energy source associated with less land use and water consumption [57], [58]. Electricity generation based on photovoltaic power can reduce most of the impact categories except for land use and terrestrial ecotoxicity which present a slight increase. The increase of land use on photovoltaic power is related to high metal resources used and the direct effect of ground-based systems. Electricity generation based on wind generation power revealed a significant reduction in all the impact categories under evaluation. Fig. 5 is a representative demonstration of the percentages of variation between the electric grid carbon intensity scenario applied to scenario S0. The percentages of reduction between impact categories for the three mobility scenarios can be seen in supplementary material S.M. 3.

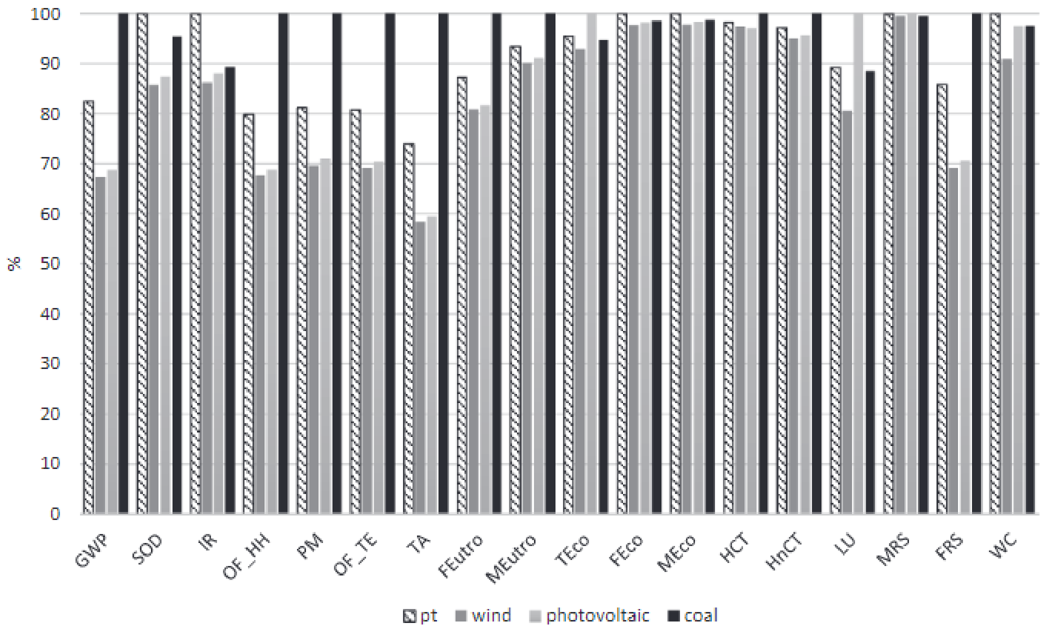

Fig. 5. Impact assessment variation of electricity generation conditions under scenario S0.

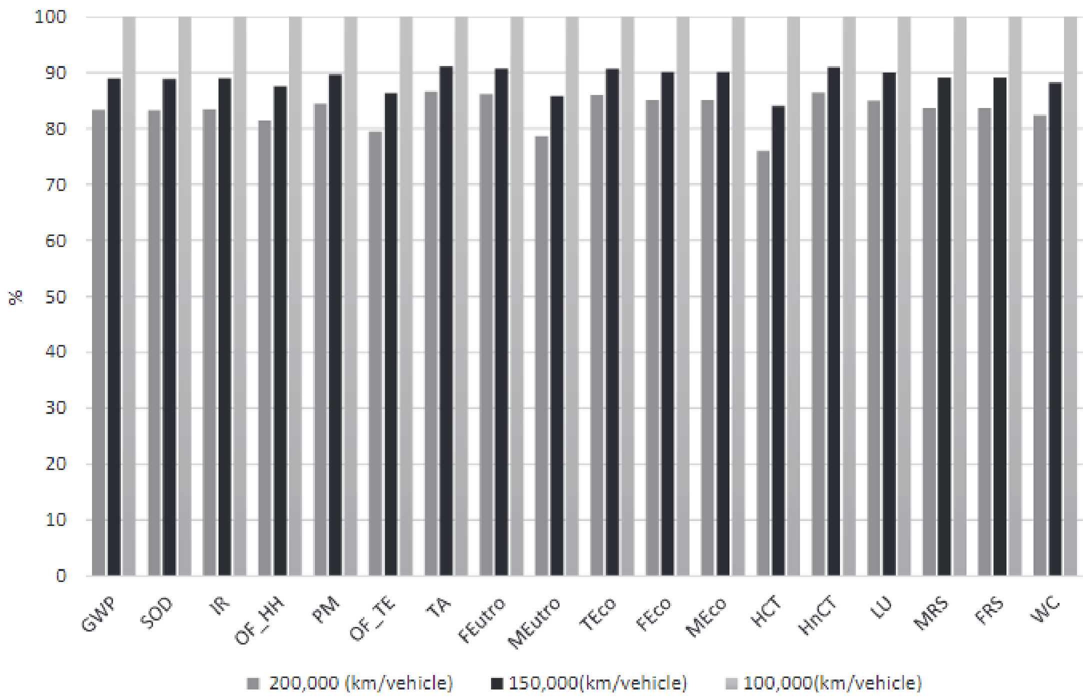

Fig. 6. Impact assessment variation of vehicle lifetime under scenario S2.

The second parameter examined was the vehicle consumption, including the automation power requirements. Considering the uncertainty related to the technological advance of automated vehicles features and their power requirements, the effect of vehicle consumption on life cycle performance was tested by varying 20% of this value. A lower bound assumes consumption of 0.163kWh/km, while an upper bound assumes consumption of 0.245kWh/km. A reduction of the vehicle consumption resulted in a maximum of 6% lower life cycle impacts, while an increase of 20% in vehicle consumption corresponds proportionally to an increase of 6% in life cycle impacts. The impact categories most affected by this variation are fossil resource scarcity and terrestrial acidification. The detailed results of this analysis can be seen on supplementary material S.M.4.

The third key parameter assumed was the vehicle lifetime. By reducing 50,000 km of vehicle lifetime it was observed an increase in the impact categories up to 19% for human carcinogenic toxicity. On the other hand, by increasing 50,000 km the impact categories decreased 3 to 5% for scenario S0 and 5 to 10% for scenarios S1 and S2. Considering a vehicle lifetime of 200,000 km, human non-carcinogenic toxicity shows a decrease of up to 10%. Fig. 6 demonstrates the variation reported for scenario S2. The detailed results of this analysis for the three scenarios under evaluation can be seen in the supplementary material S.M.5.

In sum, the sensitivity analysis demonstrates that a better life cycle performance of AEVs can be achieved if electricity generation is based on renewable sources, namely if wind generation power can be considered during the vehicle use phase (vehicle charging). Moreover, investment should be made to increase vehicle and battery lifespan.

5. CONCLUSIONS AND FUTURE WORK

This paper proposed a method to assess the life cycle environmental impact of AEVs used for private and shared mobility in an intercity context. To the best of the authors' knowledge, this is the first paper that compares shared and privately owned AEVs from a life cycle point of view and that considers the application in a regional intercity context. Moreover, this work proposed a novel methodology by combining an optimization model as input data of the LCA approach. The optimization model is used to estimate the system fleet size and usage patterns of its vehicles under a profit maximization requirement. The LCA of AEVs is then applied to the synthetic travel demand data to assess the characteristics of a privately owned fleet scenario, as well as to the results of the optimization model for two SAEV service scenarios differing in the vehicle seat capacity: 1 and 4 passengers (ridesharing).

To optimally meet the travel demand with the level of service of a privately owned vehicle, shared mobility considering a single-passenger reveal to reduce 81% of the vehicles when compared to the privately-owned fleet scenario. This reduction in fleet size has a direct effect on economic savings for society and lifecycle impacts. However, this is offset by a high vehicle intensity use.

Transitioning from a privately owned to a shared mobility system reveals a potential to reduce 20–31% of the environmental impacts under the conditions of one passenger vehicle capacity, and 32–42% under the conditions of four-passenger vehicle capacity. The impact categories with the most potential for reduction are human toxicity, mineral resource scarcity, and marine and freshwater ecotoxicity. These impact categories represent the three main areas of protection and are mainly influenced by the production phase and the vehicle wear.

Regarding the two scenarios of shared mobility, the 4-seat vehicle service can reduce over 15–16% of the environmental impacts compared to the 1-seat vehicle service, meaning no ridesharing. Indeed, the better lifecycle performance of high levels of vehicle occupancy on shared mobility is related to the reduction of the fleet. However, the use of ridesharing on shared mobility systems increases the average travel time per passenger (from 21 to 36 min) resulting from the pick-up and drop-off of extra passengers which can be an indicator of a mobility service quality reduction. Opting between ridesharing and non-ridesharing mobility system should not only consider the environmental performance but also economic and service quality aspects.

Assuming that a scenario of shared mobility using AEVs will be considered in the future of intercity mobility systems for indisputable economic and environmental reasons, special emphasis should be given to impact categories such as ozone formation, fossil resource scarcity, and global warming potential. The lower potential for reduction of these impact categories particularly depends on energy consumption and the supply chain of electricity generation. Electricity generation based on wind power is the most promising to reduce environmental impacts with the potential to reduce 27% of GWP compared to the Portuguese electricity mix. From a lifecycle perspective, the lifespan of the vehicle should be considered during the production and maintenance since diminishing this lifetime may incur a significant decrease in the lifecycle performance. On the other hand, even if the future of vehicle automation will reflect a rise in vehicle consumption, this does not seem to preclude the potential gains.

Reliable background information is offered by linking a mobility system optimization model to life cycle impact assessment. The established methodology can, in the future, provide decision-makers with comprehensive data on the environmental implications of on-demand transport services. Nowadays, considering automated and electric vehicles a developing technology, special emphasis should be given to the importance of reducing private-vehicle ownership and promoting ridesharing mobility. The potential of shared mobility can even be underestimated in this case study since it considers the optimal use of privately owned vehicles which does not reflect the reality. The global reduction of the fleet seems the most fundamental way to face environmental challenges within the road transportation sector. Furthermore, the decarbonization of electricity generation systems should be a higher global priority for the future of SAE mobility.

A limitation of performing LCA of future technologies is the lack of consistent information for inventory data; still, the results of this study provide a fair identification of impact categories. Future work should consider the expected transition whereby conventional, automated, shared and private mobility will coexist in the network environment which may diminish the potential environmental benefits [59].

ACKNOWLEDGMENTS

The authors acknowledge FICO for supplying the Xpress academic license. This work was supported by UIDB/00481/2020 and UIDP/00481/2020 - FCT - Fundação para a Ciência e a Tecnologia; and CENTRO-01-0145-FEDER-022083 - Centro Portugal Regional Operational Programme (Centro2020), under the PORTUGAL 2020 Partnership Agreement, through the European Regional Development Fund; Driving2Driverless [PTDC/ECI-TRA/31923/2017]; MobiWise [P2020 SAICTPAC/0011/2015, co-funded by COMPETE2020, Portugal2020 – Operational Program for Competitiveness and Internationalization, European Union's ERDF and FCT] and DICA-VE [POCI-01-0145-FEDER-029463]. M. Vilaça acknowledges the support of FCT for the PhD scholarship 2020.04468.BD.

REFERENCES

[1] IEA. Tracking Transport 2020, IEA, Paris. Https://www.Iea.Org/Reports/Tracking-Transport-2020: 2020.

[2] Donnellan PR. The future of mobility-Electric, autonomous, and shared vehicles. IEEE Eng Manag Rev 2018;46(4):16–8. https://doi.org/10.1109/EMR.2018.2880987.

[3] European Union. The future of road transport - Implications of automated, connected, low-carbon and shared mobility, EUR 29748 EN, Publications Office of the European Union. Publications Office of the European Union, Luxembourg 2019. https://doi.org/10.2760/668964.

[4] Rüdisüli M, Bach C, Bauer C, Beloin-Saint-Pierre D, Elber U, Georges G, et al. Prospective life-cycle assessment of greenhouse gas emissions of electricity-based mobility options. Appl Energy 2022;306:118065. https://doi.org/10.1016/j.apenergy.2021.118065.

[5] Ricardo Energy & Environment. Determining the environmental impacts of conventional and alternatively fuelled vehicles through LCA - Final Report for the European Commission, DG Climate Action [34027703/2018/782375/ETU/CLIMA.C.4]. 2020.

[6] Cox B, Bauer C, Mendoza Beltran A, van Vuuren DP, Mutel CL. Life cycle environmental and cost comparison of current and future passenger cars under different energy scenarios. Appl Energy 2020;269:1–13. https://doi.org/10.1016/j.apenergy.2020.115021.

[7] Helmers E, Weiss M. Advances and critical aspects in the life-cycle assessment of battery electric cars. Energy Emiss Control Technol 2017;5:1–18. https://doi.org/10.2147/eect.s60408.

[8] Moro A, Lonza L. Electricity carbon intensity in European Member States: Impacts on GHG emissions of electric vehicles. Transp Res Part D Transp Environ 2018;64: 5–14. https://doi.org/10.1016/j.trd.2017.07.012.

[9] Wu Z, Wang C, Wolfram P, Zhang Y, Sun X, Hertwich E. Assessing electric vehicle policy with region-specific carbon footprints. Appl Energy 2019;256:113923. https://doi.org/10.1016/j.apenergy.2019.113923.

[10] Helmers E, Dietz J, Hartard S. Electric car life cycle assessment based on real-world mileage and the electric conversion scenario. Int J Life Cycle Assess 2017;22(1): 15–30. https://doi.org/10.1007/s11367-015-0934-3.

[11] Sen B, Onat NC, Kucukvar M, Tatari O. Material footprint of electric vehicles : A multiregional life cycle assessment. J Clean Prod 2019;209:1033–43. https://doi.org/10.1016/j.jclepro.2018.10.309.

[12] Ellingsen LAW, Hung CR, Strømman AH. Identifying key assumptions and differences in life cycle assessment studies of lithium-ion traction batteries with focus on greenhouse gas emissions. Transp Res Part D Transp Environ 2017;55:82–90. https://doi.org/10.1016/j.trd.2017.06.028.

[13] Ahniyaz A, de Meatza I, Kvasha A, Garcia-Calvo O, Ahmed I, Sgroi MF, et al. Progress in solid-state high voltage lithium-ion battery electrolytes. Adv Appl Energy 2021;4:100070. https://doi.org/10.1016/j.adapen.2021.100070.

[14] Jing R, Wang J, Shah N, Guo M. Emerging supply chain of utilising electrical vehicle retired batteries in distributed energy systems. Adv Appl Energy 2021;1: 100002. https://doi.org/10.1016/j.adapen.2020.100002.

[15] Guo M, Mu Y, Jia H, Deng Y, Xu X, Yu X. Electric/thermal hybrid energy storage planning for park-level integrated energy systems with second-life battery utilization. Adv Appl Energy 2021;4:100064. https://doi.org/10.1016/j.adapen.2021.100064.

[16] Sisani F, Di Maria F, Cesari D. Environmental and human health impact of different powertrain passenger cars in a life cycle perspective. A focus on health risk and oxidative potential of particulate matter components. Sci Total Environ 2022;805:150171. https://doi.org/10.1016/j.scitotenv.2021.150171.

[17] Hawkins TR, Singh B, Majeau-Bettez G, Strømman AH. Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. J Ind Ecol 2013;17(1):53–64. https://doi.org/10.1111/j.1530-9290.2012.00532.x.

[18] Bauer C, Hofer J, Althaus HJ, Del Duce A, Simons A. The environmental performance of current and future passenger vehicles: Life Cycle Assessment based on a novel scenario analysis framework. Appl Energy 2015;157:871–83. https://doi.org/10.1016/j.apenergy.2015.01.019.

[19] Gawron JH, Keoleian GA, De Kleine RD, Wallington TJ, Kim HC. Life Cycle Assessment of Connected and Automated Vehicles: Sensing and Computing Subsystem and Vehicle Level Effects. Environ Sci Technol 2018;52(5):3249–56. https://doi.org/10.1021/acs.est.7b04576.

[20] Kemp NJ, Keoleian GA, He X, Kasliwal A. Life cycle greenhouse gas impacts of a connected and automated SUV and van. Transp Res Part D: Transp Environ 2020; 83:102375. https://doi.org/10.1016/j.trd.2020.102375.

[21] Vahidi A, Sciarretta A. Energy saving potentials of connected and automated vehicles. Transp Res Part C Emerg Technol 2018;95:822–43. https://doi.org/10.1016/j.trc.2018.09.001.

[22] Wadud Z, MacKenzie D, Leiby P. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp Res Part A Policy Pract 2016;86:1–18. https://doi.org/10.1016/j.tra.2015.12.001.

[23] Bauer GS, Greenblatt JB, Gerke BF. Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan. Environ Sci Technol 2018; 52(8):4920–8. https://doi.org/10.1021/acs.est.7b04732.

[24] Farhan J, Chen TD. Impact of ridesharing on operational efficiency of shared autonomous electric vehicle fleet. Transp Res Part C Emerg Technol 2018; 93:310–21. https://doi.org/10.1016/j.trc.2018.04.022.

[25] Narayanan S, Chaniotakis E, Antoniou C. Shared autonomous vehicle services: A comprehensive review. Transp Res Part C Emerg Technol 2020; 111:255–93. https://doi.org/10.1016/j.trc.2019.12.008.

[26] Taiebat M, Brown AL, Safford HR, Qu S, Xu M. A review on energy, environmental, and sustainability implications of connected and automated vehicles. Environ Sci Technol 2018;52:11449–65. https://doi.org/10.1021/acs.est.8b00127.

[27] Chen TD, Kockelman KM. Carsharing's life-cycle impacts on energy use and greenhouse gas emissions. Transp Res Part D Transp Environ 2016;47:276–84. https://doi.org/10.1016/j.trd.2016.05.012.

[28] Ding N, Pan J, Zhang Z, Yang J. Life cycle assessment of car sharing models and the effect on GWP of urban transportation: A case study of Beijing. Sci Total Environ 2019;688:1137–44. https://doi.org/10.1016/j.scitotenv.2019.06.111.

[29] Iacobucci R, McLellan B, Tezuka T. Costs and carbon emissions of shared autonomous electric vehicles in a Virtual Power Plant and Microgrid with renewable energy. Energy Procedia 2019; 156:401–5.

[30] Shaheen S, Cohen A, Farrar E. Carsharing's impact and future 2019; vol. 4. https://doi.org/10.1016/bs.atpp.2019.09.002.

[31] Vosooghi R, Puchinger J, Bischoff J, Jankovic M, Vouillon A. Shared Autonomous Electric Vehicle Service Performance : Assessing the Impact of Charging Infrastructure and Battery Capacity. Transp Res Part D Transp Environ 2020;81: 1–26. https://doi.org/10.1016/j.trd.2020.102283.

[32] Zhang H, Sheppard CJR, Lipman TE, Zeng T, Moura SJ. Charging infrastructure demands of shared-use autonomous electric vehicles in urban areas. Transp Res Part D Transp Environ 2020; 78:1–16. https://doi.org/10.1016/j.trd.2019.102210.

[33] Lemme RFF, Arruda EF, Bahiense L. Optimization model to assess electric vehicles as an alternative for fleet composition in station-based car sharing systems. Transp Res Part D Transp Environ 2019; 67:173–96. https://doi.org/10.1016/j.trd.2018.11.008.

[34] Martínez LM, Correia GHdA, Moura F, Mendes Lopes M. Insights into carsharing demand dynamics: Outputs of an agent-based model application to Lisbon, Portugal. Int J Sustain Transp 2017; 11(2):148–59. https://doi.org/10.1080/15568318.2016.1226997.

[35] Melendez KA, Das TK, Kwon C. Optimal operation of a system of charging hubs and a fleet of shared autonomous electric vehicles. Appl Energy 2020; 279:115861. https://doi.org/10.1016/j.apenergy.2020.115861.

[36] Santos G, Correia G. A MIP model to optimize real time maintenance and relocation operations in one-way carsharing systems. Transp Res Procedia 2015; 10:384–92. https://doi.org/10.1016/j.trpro.2015.09.088.

[37] Wang L, Liu Q, Ma W. Optimization of dynamic relocation operations for one-way electric carsharing systems. Transp Res Part C Emerg Technol 2019; 101:55–69. https://doi.org/10.1016/j.trc.2019.01.005.

[38] LaMondia JJ, Fagnant DJ, Qu H, Barrett J, Kockelman K. Shifts in long-distance travel mode due to automated vehicles: Statewide mode-shift simulation experiment and travel survey analysis. Transp Res Rec 2016; 2566(1):1–11. https://doi.org/10.3141/2566-01.

[39] Perrine KA, Kockelman KM, Huang Y. Anticipating long-distance travel shifts due to self-driving vehicles. J Transp Geogr 2020; 82:102547. https://doi.org/10.1016/j.jtrangeo.2019.102547.

[40] Santos GGD, Correia GHdA. A flow-based integer programming approach to design an interurban shared automated vehicle system and assess its financial viability. Transp Res Part C: Emerging Technol 2021; 128:103092. https://doi.org/10.1016/j.trc.2021.103092.

[41] Yu Z, Zhao P. The factors in residents' mobility in rural towns of China: Car ownership, road infrastructure and public transport services. J Transp Geogr 2021; 91:102950. https://doi.org/10.1016/j.jtrangeo.2021.102950.

[42] Huijbregts MA, Steinmann ZJ, Elshout PM, Stam G, Verones F, Vieira M, et al. ReCiPe 2016. A harmonized life cycle impact assessment method at midpoint and endpoint level. Report 1: Characterization. 2016. https://doi.org/10.1007/s11367-016-1246-y.

[43] ISO 14040. Environmental Management - Life Cycle Assessment - Principles and Framework 2006.

[44] Hawkins TR, Gausen OM, Strømman AH. Environmental impacts of hybrid and electric vehicles-a review. Int J Life Cycle Assess 2012; 17(8):997–1014. https://doi.org/10.1007/s11367-012-0440-9.

[45] Wernet G, Bauer C, Steubing B, Reinhard J, Moreno-Ruiz E, Weidema Bo. The ecoinvent database version 3 (part I): overview and methodology. Int J Life Cycle Assess 2016;21(9):1218–30.

[46] Patella SM, Scrucca F, Asdrubali F, Carrese S. Carbon Footprint of autonomous vehicles at the urban mobility system level: A traffic simulation-based approach. Transp Res Part D Transp Environ 2019; 74:189–200. https://doi.org/10.1016/j.trd.2019.08.007.

[47] CIRA. Plano Intermunicipal de Mobilidade e Transportes da Região de Aveiro - FASE 1| Relatório de Caracterização e Diagnóstico (In Portuguese) [1951/NPT-NETU-NEG/F01]. Aveiro: 2012.

[48] Furness KP. Time Function Iteration. Traffic Eng. Control 1965; 7:458–60.

[49] Google Maps. [Gloogle maps directions between Aveiro Municipality cities]. (Accessed on June, 2020) n.d. https://goo.gl/maps/BjGVuDLtKukikvJq9.

[50] European Environmental Agency (EEA). TERM 2002 29 EU - Occupancy rates of passenger vehicles. 2003.

[51] Eurostat. Electricity price statistics - Statistics Explained. https://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_price_statistics. 2018.

[52] Car depreciation - how quickly do new cars lose value? | (accessed January 11, 2021). n.d. https://www.theaa.com/car-buying/depreciation.

[53] Notter DA, Gauch M, Widmer R, W¨ager P, Stamp A, Zah R, et al. Contribution of Liion batteries to the environmental impact of electric vehicles. Environ Sci Technol 2010; 44(17):6550–6. https://doi.org/10.1021/es903729a.

[54] Renault. Novo ZOE - pequeno veículo elˊetrico [in portuguese] (Accessed on July, 2020). Renault 2019. https://www.renault.pt/veiculos-eletricos/novo-zoe.html.

[55] Simons A. Road transport: new life cycle inventories for fossil-fuelled passenger cars and non-exhaust emissions in ecoinvent v3. Int J Life Cycle Assess 2016;21(9): 1299–313. https://doi.org/10.1007/s11367-013-0642-9.

[56] International Energy Agency (IEA). World Energy Balances 2020 Edition (Database Documentation). 2020.

[57] Hertwich EG, Gibon T, Bouman EA, Arvesen A, Suh S, Heath GA, et al. Integrated life-cycle assessment of electricity-supply scenarios confirms global environmental benefit of low-carbon technologies. Proc Natl Acad Sci U S A 2015; 112(20):6277–82. https://doi.org/10.1073/pnas.1312753111.

[58] IEA. Global water consumption in the energy sector by fuel type in the Sustainable Development Scenario, 2016-2030, IEA, Paris. 2020. [59] Conceição L, Correia GHdA, Tavares JP. The reversible lane network design problem (RL-NDP) for smart cities with automated traffic. Sustain 2020; 12(3):1226. https://doi.org/10.3390/su12031226.

[59] Conceição L, Correia GHdA, Tavares JP. The reversible lane network design problem (RL-NDP) for smart cities with automated traffic. Sustain 2020; 12(3):1226. https://doi.org/10.3390/su12031226.