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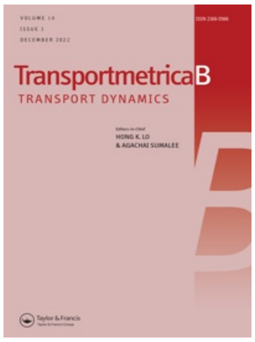

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Coupling agent-based modelling and life cycle assessment for a behaviour-driven evaluation of SAEVs

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ABSTRACT
Shared Automated Electric Vehicles (SAEVs) are poised to revolutionize future transportation. However, potential drawbacks, including increased vehicle usage and the projected shorter vehicle lifespan, introduce critical factors that may impact efficiency and environmental benefits. This research introduces a framework that integrates Agent-Based Modelling (ABM) with Life Cycle Assessment (LCA) for a behaviour-driven SAEV assessment. The ABM simulates regional SAEV operations, informing the LCA of pre- and post-integration scenarios. Sensitivity analysis on fleet sizes, system performance metrics, and Global Warming Potential (GWP) reference values are performed. Findings demonstrate that SAEVs significantly decrease the fleet size and total travel distance by raising the average travel per vehicle. SAEVs integration yields a 75–86% daily GWP reduction without significantly compromising user experience. Over 30 years, fleet replacement needs due to inadequate fleet sizing raised GWP by 170%. Balancing short and long-term environmental impact requires optimizing fleet size to achieve sustainable and efficient service delivery.

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Life cycle assessment (LCA); Agent-based modelling (ABM); Shared automated and electric vehicles (SAEVs)

1. Introduction

As the transportation sector looks for more sustainable solutions to mobility challenges, Shared Automated and Electric Vehicles (SAEVs) have emerged as a promising technology that could help reduce the environmental impact of transportation. However, to ensure that both the benefits of the technology are realized and that any unintended negative consequences are minimized, it is important to carefully analyse SAEVs from an environmental perspective.

Potential unintended consequences of SAEVs are intricately linked to the shared and automated dimension. It is expected that the maximum benefits of automation will be achieved at level 5 of automation according to the recognized standards (Society of Automotive Engineers (SAE) 2020). The standards consist of six levels, ranging from no automation (level 0) to full automation (level 5), allowing the vehicle to operate in any environmental condition or infrastructure state (SAE 2020).

In high levels of automation, the absence of a human driver not only blurs the lines between autonomous carsharing and ridesharing but also presents challenges in predicting the overall vehicle demand and their effective contribution to sustainable mobility. Indeed, SAEVs have demonstrated the potential to reduce air pollution and the number of vehicles needed to provide transportation

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services (Ding et al. 2019). This reduction has the potential to mitigate the environmental impacts associated with vehicle production and disposal, as demonstrated by Vilaça et al. (2022). However, the widespread adoption of SAEVs may bring about significant changes within the road transportation sector, potentially leading to intensive vehicle usage and a potential decline in the use of public transport alternatives (Wadud, MacKenzie, and Leiby 2016; Axsen and Sovacool 2019). These changes are primarily dependent on penetration levels, deployment strategies, and user behaviour, thereby introducing high uncertainty with far-reaching sustainable implications (Jones and Leibowicz 2019; Garus et al. 2022). Thus, it is crucial to approach this issue from an environmental standpoint, establishing connections between future deployment strategies, expected user behaviour, and environmental evaluation approaches. Recognizing the absence of extensive research on the environmental aspects of SAEVs, there is an urgent need for more comprehensive studies that can identify all necessary measures to pave the way for a sustainable future (Silva et al. 2022). In order to address the research gap, this paper proposes a methodology that merges the Agent-Based Modelling (ABM) outputs to enhance the Life Cycle Assessment (LCA) of SAEVs. ABM, a powerful tool for understanding complex systems such as transportation, provides detailed insights into user behaviours and vehicle deployment strategies, essential for understanding real-world usage patterns (Berrada and Leurent 2017; Jing et al. 2020; Li, Rombaut, and Vanhaverbeke 2021; Huang et al. 2022). LCA is widely recognized as a comprehensive methodology for assessing the environmental impacts of a product, process, or system throughout its entire life cycle (Curran 2013). However, LCA typically relies on predetermined assumptions and does not account for the dynamic and complex nature of the human decision-making process which can result in outcomes partially disrupted (Gutowski 2018). To address this ABM emerges as a valuable approach that can potentially be connected to LCA to capture the complexity and stochasticity of human behaviour (Hicks 2022). By integrating dynamic, behaviour-driven ABM outputs into LCA, a more precise assessment of the environmental footprint of SAEVs under various deployment scenarios can be achieved, ensuring a comprehensive evaluation of their sustainability impacts.

While the combination of ABM and LCA has been examined across different research fields, as discussed in the upcoming section, this paper reveals a novel application in the context of transportation, particularly focusing on SAEVs. Our primary objective is to investigate the genuine influence of user behaviour and the environmental impacts of SAEVs, offering insights not only in the short term but also over an extended time horizon. Unlike existing literature, which predominantly concentrates on urban environments, our research extends to a regional scale, encompassing both urban areas and peripheral regions characterized by low population density. This distinctive approach aims to address a notable gap in the current literature. By examining shared mobility across diverse population densities, this study aspires to provide a comprehensive understanding of the potential societal implications of SAEVs in various regions with distinct transportation needs.

In the subsequent sections, we will delve deeply into the Literature Review (Section 2) and outline our proposed integration framework, covering its key components: ABM and LCA methodology (Section 3). Section 4 will explore the specifics of input data and case study assumptions. The results and sensitivity analysis will be presented in Section 5. The ensuing discussion of findings takes stage in Section 6, providing an analysis of the implications and insights from the research. Finally, in Section 7, we conclude with a summary of key findings, contributions, research limitations, and future directions.

2. Literature Review

With advancements in automated vehicle technology reaching a significant stage and the increasing spotlight on shared and electric mobility, the scientific community has systematically explored their dimensions concerning sustainable implications. This literature review undertakes a technical journey through selected studies delving into advanced modelling methodologies for shared and automated mobility, particularly ABM, and assessing their environmental implications through LCA. The review extends to the current state of the art regarding the integration of ABM and LCA methodologies.

In short, an ABM simulates a group of independent decision-making agents operating within a defined environment and temporal context (Bonabeau 2002). Due to its bottom-up approach, it facilitates the rapid adaptation of agents' complexities, characteristics, and aggregation levels (Bonabeau 2002). Thus, ABM methodology has been widely used to represent transport systems' supply-demand interactions in different domains such as traffic flow analysis, travel behaviour modelling, transportation system planning and management, emergent technologies adoption, and possible rebound effects (e.g. Gurumurthy, Kockelman, and Loeb 2019; Soteropoulos, Berger, and Ciari 2019; Li, Rombaut, and Vanhaverbeke 2021; Huang et al. 2022; Sun, Wu, and Chen 2022). Several studies, including those by Ciari, Milos, and Axhausen (2016), Jager, Agua, and Lienkamp (2017), Becker, Ciari, and Axhausen (2018), Sheppard et al. (2019) and Wang, Correia, and Lin (2019) have employed ABM to primarily focus on the operational system performance, infrastructure requirements, impacts on the power grid, and policy assessments concerning SAEVs. These studies collectively underscore the suitability of ABM for real-world traffic simulations and offer valuable insights to support the development and deployment of future mobility systems. For instance, Jager, Agua, and Lienkamp (2017) introduced a mobility-on-demand simulation that mirrors SAEV on-demand mobility solutions at an operational level. While their primary focus was on evaluating the feasibility of operating such a system with high service levels and vehicle use, they concluded that environmental benefits should only be expected when carpooling is supported and the energy supply comes from renewable sources, underscoring the importance of concurrently assessing performance and environmental aspects. In terms of vehicle performance, SAEVs may need to relocate frequently, potentially contributing to increased congestion (Bösch, Ciari, and Axhausen 2018). A key parameter for service measurement and customer satisfaction is the average waiting time. Studies revealed that, with 95% of accepted travel demand, the waiting times could vary between 5–10 min at an urban scale (Basu et al. 2018; Gurumurthy et al. 2020). The environmental effects of non-electrified AVs will likely depend on unoccupied repositioning trips that tend to increase greenhouse gas (GHG) emissions by 25% (Lu et al. 2018). However, service level can worsen due to vehicle electrification and the type of shared system (Hyland and Mahmassani 2020; Vosooghi et al. 2020). The electrification of shared and automated vehicles holds limitations such as vehicle range and charging time, but their environmental benefits have been proven significant. It is noteworthy that the existing examinations of SAEVs, as reviewed, predominantly focus on static performance, leaving the dynamic evolution of environmental impacts throughout the SAEV lifecycle unclear (Silva et al. 2022).

Life Cycle Assessment (LCA) serves as a valuable tool for conducting a holistic environmental evaluation of SAEVs (Chen and Kockelman 2016; Gawron et al. 2018; Gawron et al. 2019; Vilaça et al. 2022). By quantifying the environmental impacts at each stage (production, use and end-of-life), LCA provides a comprehensive understanding of the sustainability of SAEVs, considering factors such as energy consumption, emissions, and resource use. This assessment helps identify hotspots and opportunities for improvement. However, the life cycle impacts of most products and processes are significantly influenced by human behaviour. In 2016, Chen and Kockelman (2016) conducted pioneering research on carsharing, bringing attention to life cycle impacts. Their study demonstrates that individuals joining a carsharing system experience an average reduction of approximately 51% in energy use and greenhouse gas (GHG) emissions. Subsequently, Gawron et al. (2018) delved into the life cycle impacts of Level 4 connected and automated vehicles. Their findings reveal a potential increase in vehicle primary energy use and GHG emissions by 3–20% due to factors such as heightened power consumption, weight, drag, and data transmission. However, the incorporation of operational effects like eco-driving and platooning results in a net reduction of up to 9% in energy and GHG emissions. Building on this research, Gawron et al. (2019) introduced a comprehensive LCA framework for automated technologies across subsystem, vehicle, and mobility-system levels. The study suggests that an automated technology fleet could cut cumulative energy and GHG emissions by 60%, primarily driven by the adoption of electrified powertrains. Additional measures, such as accelerated electrical grid decarbonization, dynamic ride-share, extended vehicle lifespan, energy-efficient computing systems, and faster fuel efficiency improvements for new vehicles, could potentially amplify these reductions to an impressive 87%. In a more recent study by Vilaça et al. (2022), the focus expands to comparing the life cycle impacts of shared and privately owned automated and electric vehicles in interurban mobility. The results not only emphasize a reduction of up to 42% in environmental impacts compared to privately owned automated vehicles but also underscore the broader importance of shared mobility systems in addressing various environmental concerns beyond GHG emissions.

Although LCA provides an in-depth approach to exploring environmental impacts, it typically relies on predetermined assumptions and does not account for the dynamic and complex nature of the human decision-making process which can result in outcomes partially disrupted (Gutowski 2018). Thus, to fully capture the complexity and stochasticity of human behaviour, ABM emerges as a valuable and significant approach that can potentially be connected to LCA (Hicks 2022). The evidence shows that combined with LCA methods, ABM offers an opportunity to gain insights into environmental impacts by a better understanding of how changes in individual behaviour and technology adoption can influence environmental outcomes (Alfaro, Sharp, and Miller 2010; Micolier et al. 2019).

Davis, Igor, and Dijkema (2009) were the first to demonstrate the integration of LCA and ABM in a proof-of-concept illustration, particularly within the field of bioelectricity. While ABM and LCA coupling has been widely applied in the energy and agriculture fields, its application in the transportation field is still relatively limited. Florent and Enrico (2015) integrated ABM into a consequential LCA to evaluate mobility-related policies; their ABM simulated the car market, including changes in car fleet composition and hourly usage patterns, which were then used to calculate the environmental and economic impacts of the policies. Onat et al. (2017) developed an ABM to estimate the future market share of electric vehicles in the United States, assessing their life-cycle environmental and economic impacts. Lu and Hsu (2017) used an ABM to simulate the market share for different transport modes (aircraft, bus, train) after the introduction of a high-speed railway. The LCA was directly integrated into the ABM model, and foreground data were obtained from existing LCA studies in the literature.

Several research gaps still exist that need to be addressed to fully realize the potential of the integration of ABM and LCA, particularly in the context of transportation. Most studies have focused on estimating the market share of different transport modes or technologies. To the authors' knowledge, no study has used this approach to explicitly model users' behaviour and emergent mobility systems such as automated or shared vehicles. This study distinctly addresses these gaps by pioneering the integrated application of ABM and LCA to evaluate the environmental impact of SAEVs. The objective of the present paper is twofold: first, to provide an ABM representation of SAEVs at a regional scale, and second, to develop a conceptual framework for integrating the ABM results into LCA to assess the environmental impacts of SAEVs. This is a unique perspective that combines the dynamic nature of ABM, which captures real-world behavioural dynamics, with the typically static and parameter-driven approach of LCA. Furthermore, our case study application focuses on a large-scale region to interpret the viability of these services in areas with low population density. This regional context is essential for understanding the social dimension of sustainability, as factors such as community acceptance and accessibility become particularly relevant. By addressing these aspects, we aim to contribute valuable insights into the potential challenges and opportunities for sustainable mobility solutions in less densely populated regions. While this study represents a pilot investigation, it serves as a crucial initial step in our ongoing research endeavours.

3. Methodology

This paper proposes a methodology that combines an ABM and LCA to assess the environmental impacts of SAEVs in a pooled ridesharing environment. The approach is designed to provide a holistic understanding of SAEVs' sustainability implications, taking into account their deployment and usage patterns. Figure 1 provides an overview of the methodological framework proposed. The methodology encompasses a comparative evaluation of the impact of SAEVs, both before and after their

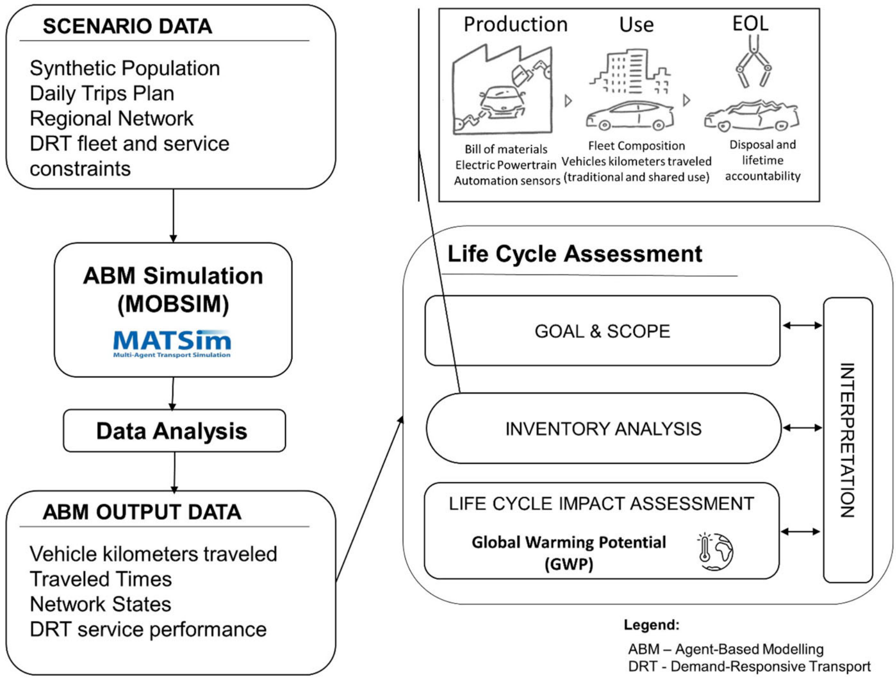

Figure 1. Methodological framework for integration of ABM into LCA.

integration into the existing mobility system. This entails constructing two ABM models: the first represents the current mobility system and the second replaces private car and bus trips with SAEVs. The ABM simulates the actual condition and SAEV deployment and usage in a case-study city or region, generating essential data for the subsequent LCA, such as, vehicle kilometres travelled and SAEV vehicle performance. The data generated by these ABM models will be subject to the inventory analysis and interpretation phase of the LCA through the analysis employing LCA reference values.

In the following sections, we will break down our methodology step by step. Section 3.1 explains how the ABM simulation was designed through MATSim simulation platform. Section 3.2 details our approach for the Life Cycle Assessment (LCA), assessing the global warming potential (GWP) impact of both scenarios. These sections provide a clear roadmap for understanding and applying the proposed framework.

3.1. ABM simulation framework

The ABM is developed using the multi-agent simulation platform MATSim – Multi-Agent Transport Simulation (Horni, Nagel, and Axhausen 2016). MATSim is an activity-based and open-source co-evolutionary model, implemented in JAVA and specially designed for large-scale scenarios. MATSim comprises three core process steps: execution, scoring, and replanning (Blamer 2007). The execution step simulates agents' movements based on their daily plans; the scoring step evaluates how each agent's plan performed by using a utility function (Charypar-Nagel), while the replanning step adapts daily plans based on the scoring process. The iterative process, derived from the scoring and replanning steps, was intentionally refrained. The absence of changes across iterations can be attributed to stable input conditions, consistent agent behaviour, and static demand patterns. This decision aligns with the research objective of conducting a straightforward and unaltered comparison between precisely defined trips. By focusing solely on static elements, this approach allows for a deeper understanding of the inherent characteristics of the transportation infrastructure, avoiding the added complexity introduced by iterative agent-level decision-making.

For initiating the MATSim simulation, a set of inputs are required: (1) a synthetic population of agents reflecting the socio-economic attributes; (2) a daily activity plan per agent, which describes the chain of activities that the agent needs to perform; (3) road network attributes and a virtual environment representative of land use and available transport services.

In this study, we have developed two different models. The first model depicts the baseline scenario closely illustrating the actual schedules reported by the population through a comprehensive survey. The baseline scenario encompasses the road trips including cars and public transport (i.e. urban buses). The second model depicts a scenario where all existing road trips are replaced by a door-to-door pooled ridesharing system designed for light-passenger vehicles. The objective of assuming the complete transition of all car trips to SAEVs is to examine a representative extreme scenario, providing a comprehensive analysis of the potential impacts associated with widespread SAEV adoption. This methodology aligns with established practices in the field, as demonstrated by studies conducted by, for example, Jager, Agua, and Lienkamp (2017); Martinez and Viegas (2017); Ciari and Becker (2017); Bischoff, Maciejewsk, and Nagel (2017); Sopjani et al. (2020); Lorig, Persson, and Michielsen (2023), who similarly employed extreme scenarios to examine the potential ramifications of transformative technological shifts in transportation. This approach allows us to assess the upper limits of the effects of SAEVs, offering insights into the system's robustness under maximal automation conditions.

3.1.1. Synthetic population and plans generation

The generation of the synthetic population aims to replicate travel patterns in alignment with established practices in ABM. The methodology begins with data preprocessing for each individual from the survey data (TIS.PT 2009). While specifics of the survey data are proprietary and not publicly available, a concise overview of essential characteristics is provided (Section 4). The survey dataset encompasses diverse information, including but not limited to, demographic details and travel behaviour patterns. Essential variables such as person ID, origin and destination coordinates, respective zone ID, travel purpose; mode of transportation; start at home; trip sequence, start time, and coefficient of expansion were extracted from the dataset. The coefficient of expansion, associated with each person ID, represents the relationship between the population in each sample extract (residential zone, age group, and gender) and the number of valid survey responses. This coefficient guides the iterative replication process for each individual, ensuring a representative synthetic population.

A Java code is developed to iteratively replicate each recorded trip in the survey dataset based on the coefficient of expansion, adding a new person ID to maintain uniqueness but keeping the original ID as well. Notably, each person typically reports more than one trip per day. For the first trip, the 'start at home' parameter, indicating the origin of each individual's first trip, is processed, offering two options: 'home' or 'other'. Sequences are analyzed to ensure the trip plans follow the reported order. The expanded records, including the replicated trips, are then systematically written to a new TSV file. This output file serves as the synthetic population dataset, possessing an expanded size compared to the original survey data. For transparency and potential debugging, the code includes optional statements to output each modified line to the console, aiding in tracking the progression of the replication process.

3.1.2. Network generation

The transportation network used in this study is derived from OpenStreetMap (OSM) data (OpenStreetMap Wiki contributors 2017), enabling a representation of the study area's road infrastructure. The process involves the transformation of OSM data into a format compatible with MATSim simulation framework. This process is facilitated by public classes and interfaces already implemented in the core utilities of MATSim: 'OsmNetworkReader', 'CoordinateTransformation', 'NetworkCleaner', 'NetworkWriter'. The 'OsmNetworkReader' class is employed to read OSM files, extract road information, and transform it into a format compatible with MATSim. This includes considerations for attributes such as lanes, free speed, and lane capacity, ensuring a realistic representation of the road network. Following the initial generation, the Network Cleaner is employed to refine the network structure. This process involves the systematic removal of redundant or inconsistent elements, enhancing the overall integrity and reliability of the network for subsequent simulation runs. Once the network is refined, the '*NetworkWriter*' class is responsible for translating the simulated network into a standard extensible markup language (XML). This step is crucial for integration with MATSim's simulation environment.

3.1.3. Demand-Responsive Transportation (DRT)

To establish the SAEVs ridesharing mode, the Demand-Responsive Transport (DRT) extensions were used to address the dynamic vehicle allocation problem (Bischoff, Maciejewsk, and Nagel 2017). The vehicle dispatch algorithm relies on an insertion heuristic, evaluating feasible insertion points for each incoming request based on constraints like capacity, time window, maximum wait time, and travel time. The goal is to optimize a given objective function (Bischoff, Maciejewsk, and Nagel 2017). In cases where multiple vehicles are capable of fulfilling the request, the system selects the most appropriate based on factors such as vehicle capacity, availability, waiting, and detour time.

The DRT mode is designed to adhere to a door-to-door scheme, providing passengers with a service closely resembling private transport. Each vehicle is configured to accommodate up to four passengers, a capacity in line with industry standards observed in ridesharing services, such as Uber, and widely accepted in shared mobility scenarios (Alonso-mora et al. 2017; Zeng et al. 2020). It is important to note that while the model assumes a maximum capacity of four persons per SAEV, this does not imply a permanent full-capacity operation. The model allows for variations in occupancy levels, reflecting real-world conditions influenced by factors such as time of day, route, and demand fluctuations. Critical time constraints of this scenario include:

- Passengers are allowed a trip duration 1.5 times longer than their original trip plus an offset of 2-hour threshold.
- Passengers are allowed to wait for DRT service pick-up for up to 20 min.

These constraints are strategically implemented to enhance the passenger experience and improve overall system efficiency. If any of these constraints are violated, the system is likely to reject the corresponding DRT requests.

3.2. Life cycle assessment

Traditional LCAs often rely on static system assumptions, providing a snapshot of the existing conditions. However, when assessing transformative technologies, such as emergent systems shaped by human behaviour, conventional LCA methods may fall short. Dynamic LCA principles guide us in incorporating behaviour-driven data, allowing us to anticipate changes as technologies evolve (e.g. Shimako et al. 2018).

In the LCA approach, data from the ABM simulation serves as input. This dataset encompasses critical aspects such as reference fleet size, vehicle movements, and users served. To assess the impact, the Global Warming Potential (GWP) impact category is selected for its widespread use in the literature and its straightforward interpretability. GWP is a metric that relates how much energy the emissions of 1 ton of a gas will absorb over a given time frame (usually 100 years), in relation to the emissions of 1 ton of carbon dioxide (CO_2) (EPA 2023; European Commission, Joint Research Centre, and Institute for Environment and Sustainability 2010). For comparison, reference values representing the life cycle GWP of internal combustion engine vehicles (ICEVs) and electric vehicles (EVs) were sourced from existing literature. Table 1 summarizes the reference values used for ICEVs and EVs, including their sources and key study characteristics. These references offer valuable insights into the primary LCA distinctions between ICEVs and EVs. In this study, the adoption of reference values serves as the foundational approach to establishing a benchmark rooted in a comprehensive dataset, ensuring comparability. The functional unit of kilogram CO_2 equivalent per kilometre (kg $CO_{2eq.}$/km) was used to quantify and compare the environmental impact assessment.

Table 1. Reference Values for ICEVs and EV lifecycle GWP ($kgCO_2eq./km$) and key reference studies characteristics.

	Study characteristics			Reference values	
Reference	Scope	Impact assessment method	Application	ICEV	EV
(Del Pero, Delogu, and Pierini 2018)	Cradle-to-Grave	Life Cycle Data System (ILCD)	ALLIANCE Project	0.203	0.129
(Sisani, Di Maria, and Cesari 2022)	Cradle-to-Grave	ILCD 2011 (MidPoint) IMPACT 2000 (EndPoint)	EURO 6 Italian Fleet	0.300	0.120
(Bieker Georg 2021)	Cradle-to-Grave	GREET tool State of Art Average data	Europe Average Vehicle Characteristics	0.248	0.085

It is important to note that specific assumptions were made in this study to enable meaningful comparisons. First, we establish a baseline scenario with all ICEVs, while the SAEVs scenario is served entirely by electric vehicles (EVs). It is assumed that connecting and automating electric vehicles would add 8% GWP due to the life-cycle impact of the sensing and computing components (Gawron et al. 2018). Additionally, private vehicles and buses were considered to use the same reference value of LCA. While it may appear that this comparison between all combustion vehicles and shared electric options is not entirely equitable, the primary purpose is to provide a range of scenarios that span from the best to the worst case. This approach helps us explore the potential environmental impact across a spectrum of possibilities and assess the potential benefits of transitioning to shared electric mobility.

4. Case-Study and Input Data

The proposed methodology is applied to a pilot study in the Coimbra Region, centre of Portugal, as illustrated in Figure 2. The figure represents the survey area outlined by TIS (2009) and the region specifically chosen for this pilot case study. The geographical area covered by the pilot study encompasses approximately 875 km^2, focusing on the most densely populated areas within the Coimbra region. In 2007, there were 177,157 residents aged 15 and above (TIS.PT 2009). The specific number of actual residents in the study area cannot be precisely determined due to the particular zone division made by the survey. However, an estimate suggests around 106,000 residents of active age in 2021 (Instituto Nacional de Estatística (INE) 2022).

The pilot case study emphasizes trips within the urban area of Coimbra and the immediately adjacent municipality zones, including those between the urban area and directly connected municipalities, as well as trips within the municipalities themselves. Trips to more distant municipalities were excluded from the analysis. The average number of daily trips per person stands at approximately 1.74, with 75% of these trips conducted by private car, 14% on foot; 7% using public transport (PT), and the remaining 4% using other less-representative modes (TIS.PT 2009). Recent studies have indicated minor changes in the modal split, with private car usage and walking trips decreasing by around 3% and PT increasing by 9% (CIM Coimbra 2016).

Travel data were sourced from the mobility survey conducted by an external entity (TIS.PT 2009). This survey was designed to cover the population residing in the municipalities of the Coimbra district and neighbouring municipalities with significant connections to Coimbra City. The survey was carried out between 2008–2009 and it was conducted by phone or at the residents' homes. Each participant was asked to describe their daily trips in detail, their modal options available and their level of satisfaction with the transport modes used (TIS.PT 2009). To maintain accuracy, only one person per household was surveyed and some questions were incorporated to characterize the household's socio-economic status. A total of 3,884 residents in the target municipalities were surveyed, from which 8,468 reported trips were analyzed and modelled, serving as the foundation for a day-representation model.

Following the synthetic population methodology, we estimated a number of 108,650 people, resulting in an estimation error of 39%. The simulation is conducted for modelling and understanding general trends rather than precise predictions. Additionally, due to the magnitude of the case study,

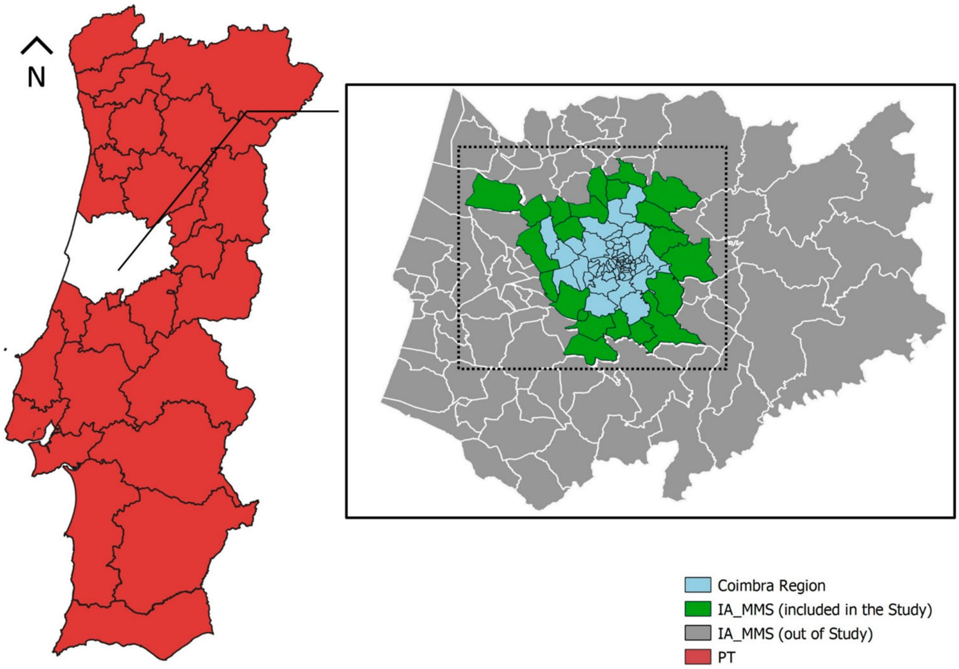

Figure 2. Pilot case study location: Coimbra region, Portugal.

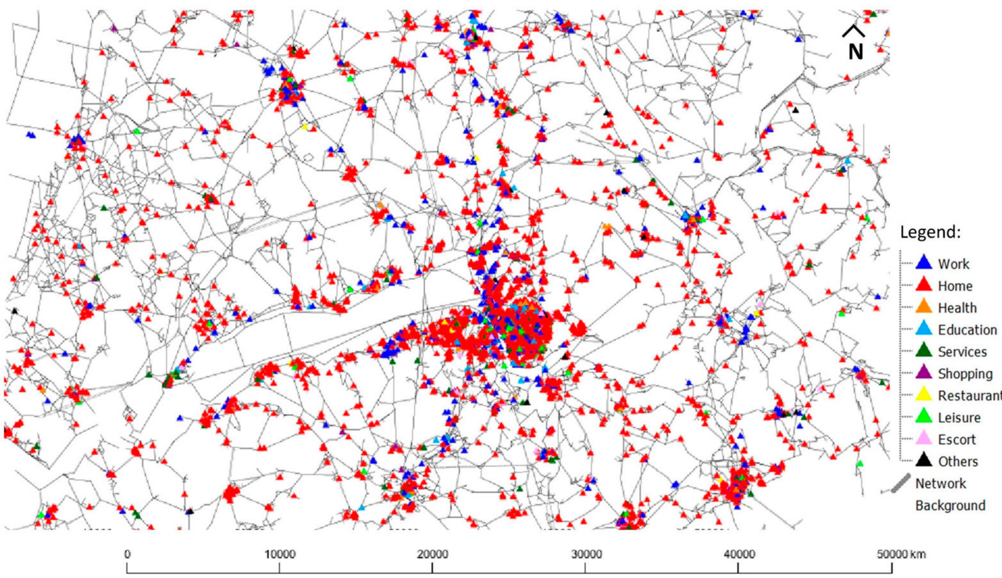

Figure 3. Representation of the facilities location and characterization.

this percentage of error is considered acceptable. From the reported survey, there is a total of 6,669 different facilities in the region. Figure 3 represents all the facilities considered in the case study and their categorization, with home and work constituting 41% and 11%, respectively.

To generate a network, data from OpenStreetMap (OSM) was converted into MATSim format. MATSim networks are composed of nodes interconnected by links, each link has several attributes,

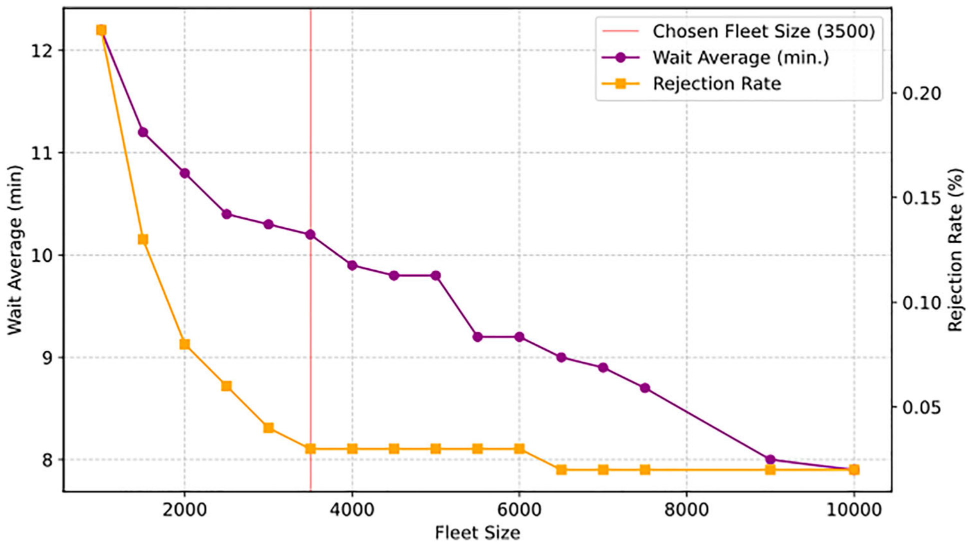

Figure 4. Relationship between SAEVs fleet size and user performance indicators.

including the number of lanes, free flow speed, and capacity. Information about PT schedules, particularly urban buses were retrieved from general transit feed specification (GTFS) files, conceded from the municipal services of urban transports of Coimbra (from Portuguese: SMTUC). There is a standard approach to importing the GTFS schedule into a MATSim PT supply that can be used for transit routing. Agents assigned to PT modes are thus able to experience realistic travel times. Trips by bike, on foot, by car, and by PT (specifically urban buses) were all modelled. However, for the study, we focused our analysis on motorized trips (car and PT) which were then replaced by SAEVs.

In the scenario involving SAEVs, all the requested trips are provided by the DRT mode, which in the context of this study represents automated and electric light passenger vehicles. The DRT fleet begins the operation from six predetermined link locations within the network. However, vehicles are not required to return to these initial points after each service, allowing for flexible routing. To determine the initial fleet size of SAEVs, a set of simulations were executed, wherein the fleet size was incrementally adjusted from 1,000 to 10,000 SAEVs. This range was selected to explore the trade-off between fleet size and key performance indicators, such as average wait times and trip rejection rates. Subsequently, the DRT fleet size selected for further analysis was based on empirical evidence gathered from these simulations. As depicted in Figure 4, the data is visually represented, and the outcomes of the analytical process are demonstrated. This process pinpointed an ideal DRT fleet size of 3,500 SAEVs. This fleet composition is used for subsequent comparison of LCA impacts against the baseline scenario. Note that, beyond the fleet size identified, the rejection rate may not experience substantial improvements (see Figure 4). This phenomenon is attributed to trips that are fundamentally challenging or impossible to complete, regardless of the fleet size. To enhance the robustness of the findings, sensitivity analyzes will be conducted to explore the implications of extreme fleet size variations.

5. Results

In this section, the results are presented, which aim to compare the baseline scenario in terms of mobility performance and LCA with the incorporation of DRT. The simulations are driven by the objective of understanding and demonstrating with this pilot-case study the potential transformative impact of DRT on regional mobility patterns and LCA. Considering the baseline scenario, 107,837 agents travelling in the region were modelled which represents a total of 231,239 trips per day. Car and PT trips

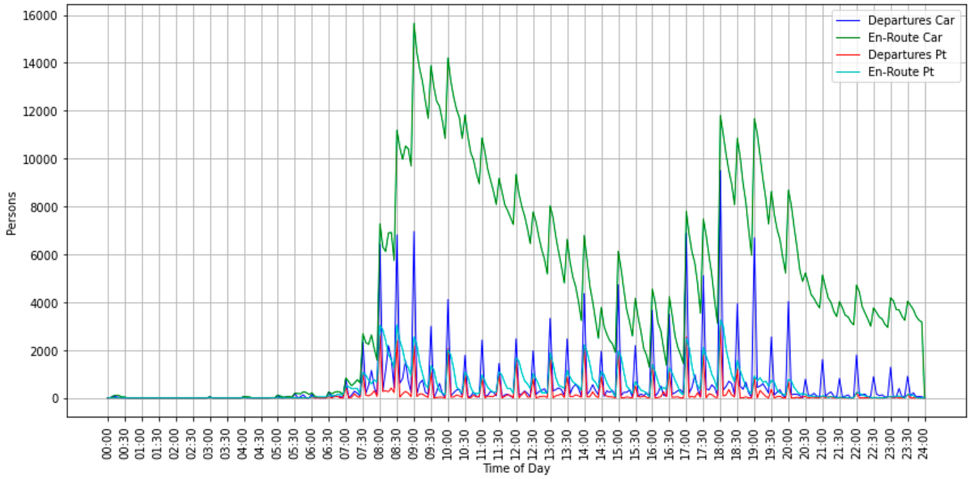

Figure 5. Distribution of car and bus trips in the Baseline Scenario.

represent 68% and 21% of all trips, respectively. Note that a small fraction, 1% of the agents' plans were found to be non-executable. This discrepancy can be attributed to incompatibilities or inaccuracies inherent in the survey data (e.g. incorrect georeferencing, updates of network context). Figure 5 illustrates the results of the simulation of the baseline scenario, depicting the distribution and peak of demand for both car and PT throughout the day. This figure is useful for understanding the variations in transportation demand and serves as a pivotal component for comparative analysis and validation. While both private cars and public transport experience peaks during rush hours (particularly 07:00–09:00 and 17:00–19:00), public transport showed a more sustained demand throughout the day. The maximum number of departures occurs between 08:00 and 09:00 with around 2829 agents departing in private cars and 3660 departures in public transport. It is noteworthy that the simulation terminates at 24:00, leading to a decline in en-route car demand. This decline may be attributed to ongoing trips that extend beyond the simulation period.

The motorized trips (car and PT) were replaced by SAEVs in the second ABM.

Table 2 presents a comparative analysis of simulation outcomes between the baseline and DRT service configurations, the latter employing a fleet of 3500 SAEVs (see Figure 4), herein referred to as DRT-base. The results demonstrate a remarkable reduction in total distance travelled (63%) and fleet size (95%) with the introduction of DRT service. Notably, the average distance travelled by individual agents increases by a mere 1% when compared to private car usage. In terms of user and operator perspectives, potential drawbacks may relate to service performance metrics, including an average user wait time of 10 min, a 3% trip rejection rate, and the observation that 22% of vehicle travel distance is unoccupied, while 66% is used at full capacity (carrying 4 passengers). Furthermore, the data reveals an 807% increase in average kilometres travelled per vehicle in the DRT-base configuration when compared to private car usage, and a 68% increase when compared to PT. These findings raise implications regarding the potential need for more frequent fleet maintenance and consequent fleet replacement in the DRT system to ensure efficient operations.

Figure 6 illustrates the total GWP in tonnes of CO_2 equivalent (tonnes CO_2 eq.) per day for both the baseline and the DRT-base scenario. It is important to emphasize that the GWP reference values for the baseline scenario are linked to ICEVs, whereas those for the DRT-base scenario are associated with EVs. As observed, the introduction of the DRT service consistently resulted in daily GWP improvements of 75%, 84%, and 86% for reference values according to Del Pero, Delogu, and Pierini (2018), Sisani, Di Maria, and Cesari (2022) and Bieker Georg (2021), respectively, highlighting the immediate positive environmental impact of the mobility service.

Table 2. Simulation Results – Baseline Scenario vs. DRT.

Scenarios	Mode	No. Trips	No. Agents	Total distance travelled (km)	Average distance per agent (km/agent)	No. Vehicles	Average distance per vehicle (km/vehicle)
Baseline	Private Car	156,147	72,426	1,164,374	16.1	72,426	16.1
	PT (urban buses)	48,524	25,909	222,317	8.6	2,552	87.1
DRT-Base	SAEVs	193,621	90,440	511,523	16.3	3,500	146.1

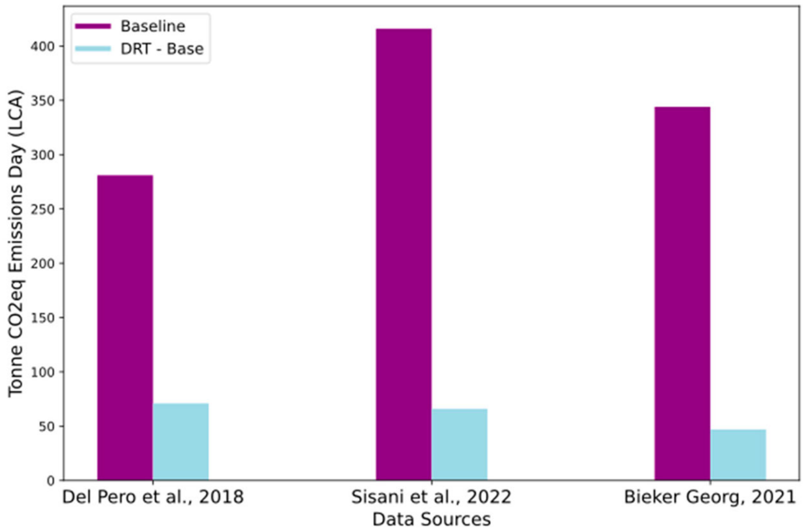

Figure 6. GWP (tonne CO_2 eq.) comparison – Baseline vs. DRT-base.

Beyond the comparison of the Baseline and DRT-base scenarios, we conducted a detailed analysis of the DRT system's performance under extreme fleet size scenarios. Starting from the DRT-base configuration (3500 SAEVs), fleets of 1000 and 10,000 SAEVs were assessed and compared (Figure 7). Adjusting the fleet size did not result in a strictly proportional increase or decrease in GWP. In comparison to the DRT-base, a 71% reduction in fleet size led to a 30% decrease in daily GWP, yet this was coupled with a decline in service quality, marked by a 23% ride rejection rate (as observed in Figure 4). Conversely, an 186% increase in fleet size decreased daily GWP by 2%, without significant changes in service performance compared to the DRT-base. It becomes evident that smaller DRT fleets showcase an enhanced capability to reduce daily GWP, while larger fleets balance the added environmental costs of more vehicles on the road with a decrease in the intensity of vehicle use. Indeed, the intensified usage resulting from a reduced DRT fleet size, as indicated by the increased average kilometres travelled per vehicle, raises concerns about potentially offsetting the observed environmental benefits due to the more frequent need for fleet replacement. To thoroughly understand these dynamics, Figure 8 displays the GWP of each fleet scenario (baseline and different DRT compositions) for a 30-year lifespan, considering a fixed vehicle lifetime of 150,000 km per vehicle (both ICEVs and EVs) as Petrauskienė, Skvarnavičiūtė, and Dvarionienė (2020). This long-term analysis, accounting for fleet replacement needs, revealed significant variations in normalized GWP values across different fleet sizes and operational intensities. Over a 30-year timeframe, the larger DRT fleet size (10,000 SAEVs) emerged as the only configuration capable of reducing GWP when compared to the baseline scenario, achieving reductions of 9–51% considering the different reference values. In contrast, the DRT-base scenario with 3500 SAEVs and the DRT scenario composed of 1000 SAEVs revealed to increase 46–170% and 150–364%, respectively.

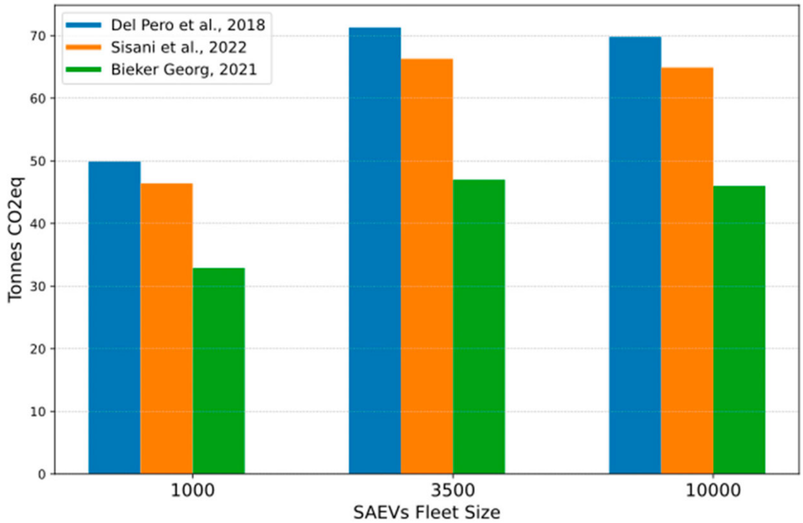

Figure 7. GWP (Tonnes CO_2 eq.) comparison of different scenarios of DRT fleet.

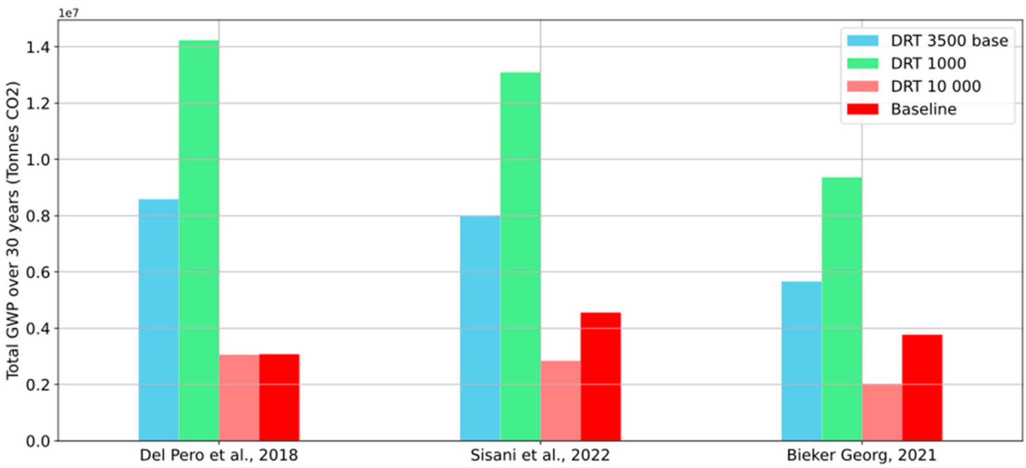

Figure 8. Total GWP (Tonnes CO_2 eq.) for each fleet scenario over 30 years timeframe.

These outcomes offer valuable insights into the implications of integrating DRT into regional mobility patterns and conducting life cycle assessment within this context. The notable observation from the simulations is the substantial impact of the DRT service on regional travel patterns, the significant decrease in overall travel distance highlights the transformative potential of DRT in influencing travel behaviour across the region. This underscores the importance of considering user daily trips information when evaluating the practicality and attractiveness of a regional DRT service. Furthermore, these insights emphasize the significance of fleet sizing in alignment with expected user behaviour, life cycle impacts, and the interrelated lifespan of the vehicles. Understanding the complex interplay between these factors is crucial for optimizing DRT operations. The life cycle assessment results underscore the need for a comprehensive approach that not only addresses immediate operational efficiency but also considers long-term sustainability and user-centric aspects.

6. Discussion

The passenger transport system is undergoing notable changes due to the increasing use of electrified and automated vehicles, alongside the growing of on-demand shared mobility. A key challenge in shaping future mobility is encountered in regions with low or sparse demand. Here, alternative on-demand solutions can play a crucial role, aligning with the three pillars of sustainability: environmental, economic, and social. Central to this research are the fundamental questions: Can the efficiency gains associated with shared and electric mobility substantially reduce LCA impacts in regions characterized by lower demand? Can sustainable mobility be promoted without compromising the user experience?

Insights from this study shed light on the consequences of integrating DRT into regional mobility patterns and conducting LCA within this context. The transition from a scenario dominated by privately owned cars to the introduction of SAEVs service reveals compelling details regarding the system's performance metrics and user experience. The substantial decrease in total distance travelled (63%) and the remarkable reduction of 95% in fleet size underscores the transformative impact of DRT. On a daily basis, this reflects a reduction of 75–86% of GWP compared to the actual scenario. However, certain performance metrics, such as rejection rate and user wait time, require attention. Strategies to address these issues may involve optimizing routes, refining scheduling algorithms, or implementing user incentives to manage demand peaks.

Assessing fleet size and the impact of these choices over a long-term period becomes pivotal. The study underscores the implications of increased kilometres travelled per vehicle in the lower fleet size DRT configuration, raising concerns about more frequent fleet maintenance and renewal needs for efficient operations. Over a 30-year horizon, the study indicates that scenarios with larger fleets could offer superior GWP benefits, whereas smaller fleets might be less advantageous, even when compared to the baseline scenario of private ICEVs. These trade-offs are more pronounced in large case studies and low-demand areas. These trends have been demonstrated by previous studies. Namely, Morfeldt and Johansson (2022), revealing that if vehicles can withstand more use without significantly impacting their lifespan, it would contribute to a substantial reduction in carbon emissions. Moreover, Saleh et al. (2022) showed that higher levels of sharing increase emissions due to empty mileage associated with vehicle relocation and higher deterioration leads to a higher fleet turnover. Beyond contributing to the understanding of the transformative impact of DRT on regional mobility, this research emphasizes the need for a comprehensive approach to optimizing SAEVs. This involves considerations for performance metrics, fleet and system sizing, user experience, and long-term environmental implications.

7. Conclusion

This paper introduces a comprehensive and integrated approach to analyse the environmental impacts of shared automated and electric vehicles (SAEVs) in interurban mobility scenarios. By combining agent-based modelling (ABM) and life cycle assessment (LCA), this study delves into the complex dynamics of Demand-Responsive Transportation (DRT) services and their relationship between mobility performance and environmental impact.

In this research, we conduct a comparative evaluation of Global Warming Potential (GWP) between the baseline and the DRT scenario, where traditional Internal Combustion Engine Vehicles (ICEVs), including private cars and buses, were replaced by SAEVs. By assuming a complete transition of all car trips to SAEVs, we aim to analyse the potential impacts of this extreme scenario, providing insights into the upper bounds of SAEV effects and assessing system robustness under maximal conditions. While we acknowledge that real-world adoption may vary, examining this extreme case offers valuable perspectives on the potential range of outcomes. The transition to SAEVs resulted in daily GWP reduction of 75%, 84%, and 86%. While promising, these reductions should be viewed within the broader context of environmental sustainability, considering user performance requirements and long-term vehicle lifetime. Moreover, adjusting the fleet sizes in the DRT system yielded non-linear GWP outcomes. Varying the fleet size in either direction did not result in a proportionate increase or decrease in GWP due to the reflection of higher intensity use (more kilometres driven by each vehicle). A crucial outcome of this research is the identification of a DRT fleet size (3500 SAEVs) that reflects the best trade-off between key performance indicators (average wait time and trips rejection rate). Beyond this fleet size, further increases had limited effects on both daily GWP and system performance. However, a 30-year perspective revealed larger fleets offered better LCA performance, reflecting less intensity use and reduced replacement needs.

These findings have significant policy implications, yet it is crucial to first acknowledge certain limitations. The study's synthetic population currently simplifies demand flows by replicating the same origin-destination pairs at the same time, potentially oversimplifying the ridesharing scenario. Future work aims to refine this by introducing a more diverse synthetic population to better represent real-world demand dynamics. Moreover, the study is constrained by the lack of a detailed lifecycle breakdown in the reference values for LCA. Future studies should aim to disaggregate GWP into distinct lifecycle phases, enhancing our understanding and enabling targeted emission mitigation strategies. Additionally, caution is warranted in extrapolating findings due to specific case study constraints, including geographical boundaries, passenger demand patterns, and operational parameters. The analysis also did not incorporate operational constraints of electric vehicles (EVs), requiring careful consideration when extending findings to other settings. Future work will extend the analysis to explore mode choice dynamics, providing valuable insights to broaden the scope and applicability of our research.

Policy implications extend beyond environmental considerations alone. Policymakers and transport planners must weigh not only the mobility benefits but also the environmental consequences when designing and implementing SAEVs services. The methodological framework proposed in this study establishes a structured approach for assessing the effective impacts of emergent mobility solutions. Recognizing the potential for skewed interpretations and greenwashing in LCA, policymakers must uphold a more substantial understanding of the holistic impact of emerging technologies. Moreover, environmental sustainability should not be pursued at the expense of social and economic equity. By employing this methodology to regulate the impacts of on-demand shared mobility, policymakers can commit to providing more equitable services, especially in rural areas. It becomes imperative to direct attention to remote areas where integrated transportation solutions might prove inadequate, even if this requires a heightened initial investment to accommodate higher fleet levels, as observed in this case study.

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References

Alfaro, Jose F., Benjamin E. Sharp, and Shelie A. Miller. 2010. "Developing LCA Techniques for Emerging Systems: Game Theory, Agent Modeling as Prediction Tools." Proceedings of the 2010 IEEE international symposium on sustainable systems and technology, ISSST 2010, 1-6. Arlington, VA, USA. https://doi.org/10.1109/ISSST.2010.5507728.

Alonso-Mora, Javier, Samitha Samaranayake, Alex Wallar, Emilio Frazzoli, and Daniela Rus. 2017. "On-Demand High-Capacity Ride-Sharing via Dynamic Trip-Vehicle Assignment." *Proceedings of the National Academy of Sciences of the United States of America* 114 (3): 462-467. https://doi.org/10.1073/pnas.1721622115.

Axsen, Jonn, and Benjamin K. Sovacool. 2019. "The Roles of Users in Electric, Shared and Automated Mobility Transitions." *Transportation Research Part D: Transport and Environment* (71): 1–21. https://doi.org/10.1016/j.trd.2019.02.012.

Basu, Rounaq, Andrea Araldo, Arun Prakash Akkinepally, Bat Hen Nahmias Biran, Kalaki Basak, Ravi Seshadri, Neeraj Deshmukh, Nishant Kumar, Carlos Lima Azevedo, and Moshe Ben-Akiva. 2018. "Automated Mobility-on-Demand vs. Mass Transit: A Multi-Modal Activity-Driven Agent-Based Simulation Approach." *Transportation Research Record* 2672 (8): 608–618. https://doi.org/10.1177/0361198118758630.

Becker, Henrik, Francesco Ciari, and Kay W. Axhausen. 2018. "Measuring the Car Ownership Impact of Free-Floating Car-Sharing – A Case Study in Basel, Switzerland." *Transportation Research Part D: Transport and Environment* 65 (December): 51–62. https://doi.org/10.1016/j.trd.2018.08.003.

Berrada, Jaâfar, and Fabien Leurent. 2017. "Modeling Transportation Systems Involving Autonomous Vehicles: A State of the Art." *Transportation Research Procedia* (27): 215–221. https://doi.org/10.1016/j.trpro.2017.12.077.

Bieker Georg. 2021. "*Global Vehicle LCA White Paper: A global comparison of the life-cycle greenhouse gas emissions of combustion engine and electric passengers cars.*" International Council on Clean Transportation (ICCT). https://theicct.org/publication/a-global-comparison-of-the-life-cycle-greenhouse-gas-emissions-of-combustion-engine-and-electric-passenger-cars/.

Bischoff, Joschka, Michal Maciejewsk, and Kai Nagel. 2017. "City-Wide Shared Taxis: A Simulation Study in Berlin." IEEE conference on intelligent transportation systems, proceedings, ITSC, 2018-March: 275–280. Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/ITSC.2017.8317926.

Blamer, Michael. 2007. "Travel Demand Modeling for Multi-Agent Transport Simulations: Algorithms and Systems [DISS. ETH NO. 17238] (Unpublished Doctoral Dissertation)." ETH Zurich.

Bonabeau, Eric. 2002. "Agent-Based Modeling: Methods and Techniques for Simulating Human Systems." *Proceedings of the National Academy of Sciences of the United States of America* 99 (SUPPL. 3): 7280–7287. https://doi.org/10.1073/pnas.082080899.

Bösch, Patrick M., Francesco Ciari, and Kay W. Axhausen. 2018. "Transport Policy Optimization with Autonomous Vehicles." *Transportation Research Record* 2672 (8): 698–707. https://doi.org/10.1177/0361198118791391.

Chen, T. Donna, and Kara M. Kockelman. 2016. "Carsharing's Life-Cycle Impacts on Energy Use and Greenhouse Gas Emissions." *Transportation Research Part D: Transport and Environment* (47): 276–284. https://doi.org/10.1016/j.trd.2016.05.012.

Ciari, Francesco, and Henrik Becker. 2017. "How Disruptive Can Shared Mobility Be? A Scenario-Based Evaluation of Shared Mobility Systems Implemented at Large Scale." In *Disrupting Mobility. Lecture Notes in Mobility*, edited by G. Meyer, and S. Shaheen. Springer. doi:https://doi.org/10.1007978-3-319-51602-8_3.

Ciari, Francesco, Balac Milos, and Kay W. Axhausen. 2016. "Modeling Carsharing with the Agent-Based Simulation MATSim." *Transportation Research Record: Journal of Transportation Research Board* 2564: 14–20. https://doi.org/10.3142/2564-02.

CIM Coimbra. 2016. *Plano Intermunicipal de Mobilidade e Transportes Da Região de Aveiro - PRT 186-02-07 V03.00 (In Portuguese)*. *Relatório de Caracterização e Diagnóstico*. Vol. Fase 1.

Curran, Mary Ann. 2013. "Life Cycle Assessment: A Review of the Methodology and Its Application to Sustainability." *Current Opinion in Chemical Engineering* 2 (3): 273–277. https://doi.org/10.1016/j.coche.2013.02.002.

Davis, Chris, Nikolic Igor, and Gerard P J Dijkema. 2009. "Integration of Life Cycle Assessment Into Agent-Based Modeling." *Journal of Industrial Ecolog* 13 (2), https://doi.org/10.1111/j.1530-9290.2009.00122.x.

Del Pero, Francesco, Massimo Delogu, and Marco Pierini. 2018. "Life Cycle Assessment in the Automotive Sector: A Comparative Case Study of Internal Combustion Engine (ICE) and Electric Car." In *Procedia Structural Integrity; International Conference on Stress Analysis (AIAS 2018)*, 521–537. Elsevier B.V. https://doi.org/10.1016/j.prostr.2018.11.066.

Ding, Ning, Jingjin Pan, Zhan Zhang, and Jianxin Yang. 2019. "Life Cycle Assessment of Car Sharing Models and the Effect on GWP of Urban Transportation: A Case Study of Beijing." *Science of the Total Environment* (688): 1137–1144. https://doi.org/10.1016/j.scitotenv.2019.06.111.

EPA. 2023. "Understanding Global Warming Potentials." https://www.epa.gov/ghgemissions/understanding-global-warming-potentials.

European Commission, Joint Research Centre, and Institute for Environment and Sustainability. 2010. *International Reference Life Cycle Data System (ILCD) Handbook [EUR 24708 EN] General Guide for Life Cycle Assessment - Detailed Guidance*. Luxemburg.

Florent, Querini, and Benetto Enrico. 2015. "Combining Agent-Based Modeling and Life Cycle Assessment for the Evaluation of Mobility Policies." *Environmental Science and Technology* 49 (3), https://doi.org/10.1021/es5060868.

Garus, Ada, Borja Alonso, Maria Alonso Raposo, Biagio Ciuffo, and Luigi Dell'olio. 2022. "Impact of New Mobility Solutions on Travel Behaviour and Its Incorporation Into Travel Demand Models." *Journal of Advanced Transportation* 2022. https://doi.org/10.1155/2022/7293909.

Gawron, James H., Gregory A. Keoleian, Robert D. De Kleine, Timothy J. Wallington, and Hyung Chul Kim. 2018. "Life Cycle Assessment of Connected and Automated Vehicles: Sensing and Computing Subsystem and Vehicle Level Effects." *Environmental Science and Technology* (52): 3249–3256. https://doi.org/10.1021/acs.est.7b04576.

Gawron, James H., Gregory A. Keoleian, Robert D. De Kleine, Timothy J. Wallington, and Hyung Chul Kim. 2019. "Deep Decarbonization from Electrified Autonomous Taxi Fleets: Life Cycle Assessment and Case Study in Austin, TX." *Transportation Research Part D: Transport and Environment* (73): 130–141. https://doi.org/10.1016/j.trd.2019.06.007.

Gurumurthy, Krishna Murthy, Felipe de Souza, Annesha Enam, and Joshua Auld. 2020. "Integrating Supply and Demand Perspectives for a Large-Scale Simulation of Shared Autonomous Vehicles." *Transportation Research Record* 2674 (7): 181–192. https://doi.org/10.1177/0361198120921157.

Gurumurthy, Krishna Murthy, Kara M. Kockelman, and Benjamin J. Loeb. 2019. *Sharing Vehicles and Sharing Rides in Real-Time: Opportunities for Self-Driving Fleets. Advances in Transport Policy and Planning. 1st ed. Vol. 4*. Elsevier Inc. https://doi.org/10.1016/bs.atpp.2019.09.001.

Gutowski, Timothy G. 2018. "A Critique of Life Cycle Assessment; Where Are the People?" Procedia CIRP: life cycle engineering (LCE) conference, 69: 11–15. Copenhagen, Denmark: Elsevier. https://doi.org/10.1016/j.procir.2018.01.002.

Hicks, Andrea. 2022. "Seeing the People in LCA: Agent Based Models as One Possibility." *Resources, Conservation & Recycling Advances* 15 (200091). https://doi.org/10.1016/J.RCRADV.2022.200091.

Horni, Andreas, Kai Nagel, and Kay W Axhausen, eds. 2016. *The Multi-Agent Transport Simulation MATSim*. London: Ubiquity Press. https://doi.org/10.5334/baw.

Huang, Jiangyan, Youkai Cui, Lele Zhang, Weiping Tong, Yunyang Shi, and Zhiyuan Liu. 2022. "An Overview of Agent-Based Models for Transport Simulation and Analysis." *Journal of Advanced Transportation* 2022 (1252534): 1-17https://doi.org/10.1155/2022/1252534.

Hyland, Michael, and Hani S. Mahmassani. 2020. "Operational Benefits and Challenges of Shared-Ride Automated Mobility-on-Demand Services." *Transportation Research Part A: Policy and Practice* (134): 251–270. https://doi.org/10.1016/j.tra.2020.02.017.

Instituto Nacional de Estatística (INE). 2022. "Censos 2021. XVI Recenseamento Geral Da População. VI Recenseamento Geral Da Habitação: Resultados Definitivos (In Portuguese)." Lisbon. https://www.ine.pt/xurl/pub/65586079.

Jager, Benedikt, Fares Maximilian Mrad Agua, and Markus Lienkamp. 2017. "Agent-Based Simulation of a Shared, Autonomous and Electric on-Demand Mobility Solution." IEEE conference on intelligent transportation systems, proceedings, ITSC, 250–255. https://doi.org/10.1109/ITSC.2017.8317947.

Jing, Peng, Hanbin Hu, Fengping Zhan, Yuexia Chen, and Yuji Shi. 2020. "Agent-Based Simulation of Autonomous Vehicles: A Systematic Literature Review." *IEEE Access* 8: 79089–79103. https://doi.org/10.1109/ACCESS.2020.2990295.

Jones, Erick C., and Benjamin D. Leibowicz. 2019. "Contributions of Shared Autonomous Vehicles to Climate Change Mitigation." *Transportation Research Part D: Transport and Environment* (72): 279–298. https://doi.org/10.1016/j.trd.2019.05.005.

Li, Jingjun, Evy Rombaut, and Lieselot Vanhaverbeke. 2021. "A Systematic Review of Agent-Based Models for Autonomous Vehicles in Urban Mobility and Logistics: Possibilities for Integrated Simulation Models." *Computers, Environment and Urban Systems* (89): 101686. https://doi.org/10.1016/j.compenvurbsys.2021.101686.

Lorig, Fabian, Jan A. Persson, and Astrid Michielsen. 2023. "Simulating the Impact of Shared Mobility on Demand: A Study of Future Transportation Systems in Gothenburg, Sweden." *International Journal of Intelligent Transportation Systems Research* 21 (1): 129–144. https://doi.org/10.1007/S13177-023-00345-5/TABLES/8.

Lu, Miaojia, and Shu-Chien Hsu. 2017. "Spatial Agent-Based Model for Environmental Assessment of Passenger Transportation." *Journal of Urban Planning and Development* 143 (4): 1–11. https://doi.org/10.1061/(asce)up.1943-5444.0000403.

Lu, Miaojia, Morteza Taiebat, Ming Xu, and Shu-Chien Hsu. 2018. "Multiagent Spatial Simulation of Autonomous Taxis for Urban Commute: Travel Economics and Environmental Impacts." *Journal of Urban Planning and Development* 144 (4), https://doi.org/10.1061/(asce)up.1943-5444.0000469.

Martinez, Luis M., and José Manuel Viegas. 2017. "Assessing the Impacts of Deploying a Shared Self-Driving Urban Mobility System: An Agent-Based Model Applied to the City of Lisbon, Portugal." *International Journal of Transportation Science and Technology* 6: 13–27. https://doi.org/10.1016/j.ijtst.2017.05.005.

Micolier, Alice, Philippe Loubet, Franck Taillandier, and Guido Sonnemann. 2019. "To What Extent Can Agent-Based Modelling Enhance a Life Cycle Assessment? Answers Based on a Literature Review." *Journal of Cleaner Production* (239): 118123. https://doi.org/10.1016/J.JCLEPRO.2019.118123.

Morfeldt, Johannes, and Daniel J.A. Johansson. 2022. "Impacts of Shared Mobility on Vehicle Lifetimes and on the Carbon Footprint of Electric Vehicles." *Nature Communications* 13 (1): 1–11. https://doi.org/10.1038/s41467-022-33666-2.

Onat, Nuri C., Mehdi Noori, Murat Kucukvar, Yang Zhao, Omer Tatari, and Mikhail Chester. 2017. "Exploring the Suitability of Electric Vehicles in the United States." *Energy* 121: 631–642. https://doi.org/10.1016/J.ENERGY.2017.01.035.

OpenStreetMap Wiki contributors. 2017. "Researcher Information." *OpenStreetMap Wiki,*. https://export.hotosm.org/en/v3/.

Petrauskienė, Kamilė, Monika Skvarnavičiūtė, and Jolanta Dvarionienė. 2020. "Comparative Environmental Life Cycle Assessment of Electric and Conventional Vehicles in Lithuania." *Journal of Cleaner Production* 246. https://doi.org/10.1016/j.jclepro.2019.119042.

Saleh, Marc, Alexandre Milovanoff, I. Daniel Posen, Heather L. MacLean, and Marianne Hatzopoulou. 2022. "Energy and Greenhouse Gas Implications of Shared Automated Electric Vehicles." *Transportation Research Part D: Transport and Environment* (105): 103233. https://doi.org/10.1016/j.trd.2022.103233.

Sheppard, Colin J.R., Gordon S. Bauer, Brian F. Gerke, Jeffery B. Greenblatt, Alan T. Jenn, and Anand R. Gopal. 2019. "Joint Optimization Scheme for the Planning and Operations of Shared Autonomous Electric Vehicle Fleets Serving Mobility on Demand." *Transportation Research Record* 2673 (6): 579–597. https://doi.org/10.1177/0361198119838270.

Shimako, Allan Hayato, Ligia Tiruta-Barna, Ana Barbara Bisinella de Faria, Aras Ahmadi, and Mathieu Spérandio. 2018. "Sensitivity Analysis of Temporal Parameters in a Dynamic LCA Framework." *Science of the Total Environment* 624: 1250–1262. https://doi.org/10.1016/j.scitotenv.2017.12.220.

Silva, Óscar, Rubén Cordera, Esther González-González, and Soledad Nogués. 2022. "Environmental Impacts of Autonomous Vehicles: A Review of the Scientific Literature." *Science of the Total Environment* 830), https://doi.org/10.1016/j.scitotenv.2022.154615.

Sisani, Federico, Francesco Di Maria, and Daniela Cesari. 2022. "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." In *Science of The Total Environment* 805 (150171). https://doi.org/10.1016/J.SCITOTENV.2021.150171.

Society of Automotive Engineers (SAE). 2020. *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles.* Vol. J3216_2020.

Sopjani, Liridona, Jenny Janhager Stier, Mia Hesselgren, and Sofia Ritzén. 2020. "Shared Mobility Services versus Private Car: Implications of Changes in Everyday Life." *Journal of Cleaner Production* (259): 120845. https://doi.org/10.1016/J.JCLEPRO.2020.120845.

Soteropoulos, Aggelos, Martin Berger, and Francesco Ciari. 2019. "Impacts of Automated Vehicles on Travel Behaviour and Land Use: An International Review of Modelling Studies." *Transport Reviews* 39 (1): 29–49. https://doi.org/10.1080/01441647.2018.1523253.

Sun, Ruixiao, Xuanke Wu, and Yuche Chen. 2022. "Assessing the Impacts of Ridesharing Services: An Agent-Based Simulation Approach." *Journal of Cleaner Production* (372): 133664. https://doi.org/10.1016/J.JCLEPRO.2022.133664.

TIS.PT. 2009. *Inquérito à Mobilidade Na Área de Influência Do Sistema de Mobilidade Do Mondego [1507/4-02/PT]. TiS.PT*. Coimbra.

Vilaça, Mariana, Gonçalo Santos, Mónica S.A. Oliveira, Margarida C. Coelho, and Gonçalo H.A. Correia. 2022. "Life Cycle Assessment of Shared and Private Use of Automated and Electric Vehicles on Interurban Mobility." *Applied Energy* (310): 118589. https://doi.org/10.1016/j.apenergy.2022.118589.

Vosooghi, Reza, Jakob Puchinger, Joschka Bischoff, Marija Jankovic, and Anthony Vouillon. 2020. "Shared Autonomous Electric Vehicle Service Performance : Assessing the Impact of Charging Infrastructure and Battery Capacity." *Transportation Research Part D: Transport and Environment* 81 (102283): 1–26. https://doi.org/10.1016/j.trd.2020.102283.

Wadud, Zia, Don MacKenzie, and Paul Leiby. 2016. "Help or Hindrance? The Travel, Energy and Carbon Impacts of Highly Automated Vehicles." *Transportation Research Part A: Policy and Practice* 86: 1–18. https://doi.org/10.1016/j.tra.2015.12.001.

Wang, Senlei, Goncalo Homem De Almeida Correia, and Hai Xiang Lin. 2019. "Exploring the Performance of Different On-Demand Transit Services Provided by a Fleet of Shared Automated Vehicles: An Agent-Based Model." *Journal of Advanced Transportation*, https://doi.org/10.1155/2019/7878042.

Zeng, Weiliang, Yu Han, Weijun Sun, Shengli Xie, and Weiliang Zeng. 2020. "Exploring the Ridesharing Efficiency of Taxi Services." *IEEE Access* 8: 160396–160406. https://doi.org/10.1109/ACCESS.2020.3020861.