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Assessing sustainability of smart last mile delivery: a simulation-based decision support tool

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ABSTRACT

The increasing demand of e-commerce is forcing economic and environmental inefficiency in last mile logistics (LML). The adoption of smart and autonomous technologies, such as Unmanned Aerial Vehicles (UAVs) and Autonomous Delivery Robots (ADRs), is being evaluated in LML in order to increase its effectiveness. UAVs offer advantages such as faster delivery times and reduced traffic congestion, but face challenges like weather sensitivity and the need for dedicated take-off and landing infrastructure. ADRs can reduce emissions and operational costs compared to traditional LML systems, but their full application is limited mainly due to slower speeds and complex interactions with pedestrians. Despite their limitations, in future years these technologies could be fully applied for LML: thus, evaluating their environmental impact during LML service is necessary to plan their full-scale application. This study proposes a simulation-based decision support tool for assessing the performance of traditional and smart LML technologies according to economic and environmental points of view. By leveraging advanced simulation models, the proposed tool allows to estimate these impacts under varying operational conditions, providing a comprehensive framework for decision-making the LML field by comparing traditional versus innovative LML services. The tool was validated through a case study application in an urban context, demonstrating its ability to highlight the potential benefits and challenges of applying UAVs and ADRs into LML networks. Results indicate that unmanned delivery vehicles allow for a substantial reduction in carbon emissions in the operational phase, confirming their potential as a more environmentally sustainable solution for urban last mile logistics. In addition, the total cost associated with unmanned systems is found to be comparable to that of conventional vehicles, particularly when these latter operate under medium-to-high traffic conditions. Researchers and logistic companies can use this tool to evaluate and optimize the impact of their innovative LML services strategies and achieve improved economic and environmental sustainability levels.

1. Introduction

Last mile logistics (LML) is currently the most inefficient segment of urban logistic [1]: a recent study [2], has outlined as, while representing <5 % of the entire distance for delivering goods to customers, the average transport time is around 5 h. Furthermore, last mile delivery is characterized by the highest cost factor, as it determines about 70 % of the total logistic costs [3]. Several factors are contributing to these results, such as the growing increase of online sales causing an increase in the number of delivered parcels [4], together with exponential increase for quick delivery services requested by final customers [5,6]

Thus, e-commerce accounts for over 70 % of European Courier Express Parcels volumes, and last mile delivery and packaging accounts for 40 % of all e-commerce emissions [7]. Currently, last mile deliveries are carried out almost exclusively by traditional vehicles – i.e., internal combustion ones -, and, consequently, causing a high level of carbon equivalent (CO_{2eq}) emissions [8]; in addition, a recent report forecasts about a 32 % increase in carbon emissions from urban delivery traffic by 2030 [9].

Several research and policy efforts have been oriented to reduce these impacts by evaluating new models, strategies, and operative tools that could contribute to improve sustainability levels of LML services. An important contribution could be derived from the implementation of new smart technologies [6,10]; among these, logistic systems based on autonomous deliveries [11], that can be defined as smart last mile logistics (SLML), could represent an opportunity to improve the efficiency

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and sustainability of last mile operations. These technologies include Autonomous Delivery Robots (ADRs) and Unmanned Aerial Vehicles (UAVs), which could be used for last mile deliveries and return activities [12]. These technologies provide numerous benefits, including reduced delivery times [13,14], cost savings [15], and decreased traffic congestion [16]. However, critical technical challenges remain unresolved, such as batteries management, the need for dedicated take-off and landing facilities for UAVs [17], and operational constraints like payload optimization and route efficiency [18]. In this research field, simulation modelling has been recently applied to solve some of these challenges. In detail, Cokyasar et al. [19] developed a UAV network design model including the problem related to automated battery-swapping stations, demonstrating the applicability of simulation models to enhance the operational availability of UAV fleets. Similarly, Huang et al. [20] explored optimal locations for charging stations and battery-swapping facilities through simulation, highlighting the significant impact of infrastructure placement on operational efficiency. Other studies applied simulation modelling for optimizing performance of these innovative logistics network. Schnieder and West [21] proposed a simulation-based decision support system for optimizing the number and placement of pick-up points for ADRs. Furthermore, Poeting et al. [22] and Swanson [23] applied simulation to assess the operational performance of various innovative delivery strategies, with Swanson's study particularly emphasizing on how UAV adoption can minimize total delivery time.

However, less attention has been dedicated to evaluating the environmental impact of these delivery systems. Khalid and Chankov [24] have adopted simulation modelling to assess the sustainability level of SLML systems in a holistic manner by integrating drones with public transport and comparing them with truck delivery across multiple scenarios, analysing service level, delivery time, CO2 emissions, and utilization. This highlights the need for comprehensive tools that not only assess operational performance but also account for economic and environmental impacts, bridging the gap in the current literature.

With the aim of contributing to fill this gap, this study seeks to address the following two research questions (RQ):

RQ 1: How can a simulation-based decision support tool enhance the design and assessment of smart LML systems?

RQ 2: What are the comparative benefits and limitations of innovative technologies, such as Unmanned Aerial Vehicles (UAVs) and Autonomous Delivery Robots (ADRs), versus traditional delivery services from an economic and environmental point of view?

Thus, this study proposes a simulation-based decision support tool designed to evaluate the sustainability of various LML technologies. Unlike previous studies that primarily focus on operational performance, this tool integrates economic and environmental metrics to compare traditional (e.g., Internal combustion engine vehicles – ICEVs, Electric vans - E-vans) and innovative (e.g., UAVs, ADRs) technologies, not only assessing economic and environmental performance but also providing decision-makers with insights for the optimization of urban logistics strategies. Compared to previous studies, this research combines scenario-based simulation with dynamic variables, such as traffic conditions and parcel demand, thereby offering a more comprehensive and comparative analysis of last mile delivery options. Through this method, the study aims not only to assess technologies, but also to support strategic decision-making for urban logistics planning.

The tool has been validated through a case study, comparing different delivery options based on SLML as well as traditional delivery systems. By modelling and evaluating different scenarios, the performance of each delivery systems has been evaluated from an economic and environmental point of view, aiming to support decision-making for a more sustainable LML services.

The structure of the paper is as follows: in Section 2, a state of the art about the use of smart technologies in LML is discussed; next, the proposed model is discussed in Section 3. Results are presented in Section 4 and finally discussions and conclusions are outlined in Sections 5 and 6.

2. Sustainable and smart technologies in last mile logistics: a quick state of the art

LML refers to the final step in the delivery process, connecting distribution centres to end customers. This segment of the supply chain is often the most inefficient and costly, due to factors like fragmented delivery networks, high variability in customer demand, and urban traffic congestion. A sustainable LML system must address these inefficiencies while balancing economic, environmental, and operational goals. Therefore, critical success factors usually include reducing delivery time and costs, optimizing vehicle routes, minimizing greenhouse gas emissions, and integrating advanced technologies to meet growing e-commerce demands.

To establish a solid foundation for the proposed work, this study builds upon a comprehensive review of previous literature, focusing on simulation-based evaluations of innovative technologies in last mile delivery systems. The aim is to highlight the most critical elements that could affect the performance of each technology from an economic and an environmental point of view; these elements will be used for developing the proposed decision support tool described in the next section.

2.1. E-van adoption in last mile logistic

The advancement of transportation systems through electrification is playing a crucial role, especially in LML. Conventional ICEV delivery is currently a significant contributor to traffic and air pollution in urban areas [25]. Thus, several normative regulations are forcing the massive adoption of E-vans, which could help to reduce emissions [26–28] consequently improving air quality [29].

These solutions must be also evaluated from an economic perspective to assess their sustainability levels. Several recent papers analyse the economic dimension of the problem. One critical factor is the high initial investment costs required for E-vans fleets and equipment [30,31]. On the other side, Siragusa et al. [27] outlined as, by comparing these systems with ICEV through a life cycle cost model, the higher initial investment cost must be compared to the lower fuel and energy cost that allows a competitive advantage [32]. This is also confirmed by Pahwa and Jaller [33], who focused on other savings derived from the use of E-vans due to lower maintenance costs, repair costs, and power costs. Similar findings are presented by Akkad et al. [34] who discussed how the adoption of E-vans compared to conventional ICEV systems can result in a reduction in the total energy required to complete the single delivery journey.

Together with positive impacts, some criticalities have been also highlighted in the scientific literature. The integration of E-vans into delivery fleets introduces a novel dimension to route planning, as it necessitates consideration of recharge station availability along the planned routes [35]. Route optimization algorithms must now factor in the location of recharge stations to ensure that delivery routes are both time-efficient and compatible with the charging infrastructure [36]. This inclusion of recharge stations in route planning aims to minimize disruptions and maximize the utilization of E-vans, while mitigating concerns about range limitations [37].

Moreover, the insufficient availability of charging stations in some urban context can represent an obstacle to the widespread adoption of E-vans, requiring infrastructural interventions to ensure uninterrupted delivery journeys [38]. The low density of charging infrastructure affects the convenience and practicality of using E-vans [39].

Another obstacle outlined in the scientific literature is the battery autonomy of the E-van together with long re-charging time, which could sometimes represent a limitation in its full adoption in several real contexts [40]. A recent study [41] has discussed a different perspective trough a specific case study: their results showed that the delivery service could be completed with the same performance by an E-van or an ICEV, as there is no need to recharge the E-van batteries during the shift. Siragusa et al. [27] proposed a research study in which it simulates different proportions of E-vans in a delivery fleet for last mile obtaining a diminution in greenhouse gas (GHG) when E-vans are used, especially when a higher daily mileage is required.

2.2. Unmanned aerial vehicles for delivery (UAV)

UAV delivery in last mile is not fully developed yet in the current market; the introduction of UAV delivery in LML heralds a disruptive innovation with the potential to redefine traditional delivery systems. Recent studies have discussed the strategic dimension of the problem, which includes airspace utilization [42], payload capacity, privacy issues [43] and flight environment burdens [44]. Furthermore, the social acceptance is another challenging topic: one example is the perceived risk level associated with UAV adoption. In line with this topic, recently, a discussion about how to reduce collision risks for last mile package delivery has been proposed by Chen et al. [45]. Although these criticalities are still present, public acceptance of this service seem to be high, mainly due to the increased delivery speed provided by UAVs services [14].

As this service is very innovative, several studies focus on evaluating its economic dimension, which is characterized by high uncertainty. Yuan and Herve [46] discussed the composition of initial investment and operational expenses, including landing hub management costs. In this case overall infrastructure costs – e.g. landing hubs, control software systems – have a higher impact in the short term compared to traditional delivery services; Aurambout et al. [17] argued that, in the long-term operational savings could overcome these new expenses. Thus, operational cost analysis has been discussed in some papers. Since UAVs do not use "traditional" road infrastructures, some authors estimated a reduction in overall operational phase costs compared with ICEV and E-van [47], also in terms of vehicle maintenance, and labour expenses connected to ground-based deliveries [48]. However, new costs must be evaluated for these delivery systems, such as battery replacement, missed delivery due to weather conditions and compliance with aviation regulations.

Hybrid solutions – i.e., where UAVs are integrated with traditional delivery systems – have been also analysed [49] proposed the adoption of well know travelling salesman model for integrating delivery carried out in coordination between UAVs and trucks. The results obtained pointed out the economic convenience of this solution in such a scenario. Similarly, in Salama and Srinivas [50] customer clustering and optimized vehicle routing have been adopted to minimize delivery costs and order completion time [51]propose a green vehicle routing problem to assess the energy efficiency of hybrid UAV and ICEVs delivery models.

Some studies [52,53] have outlined that the adoption of UAV delivery services in LML services could contribute to reduce greenhouse gas emissions mainly through their electric propulsion systems. Like for E-vans, the adoption of electric propulsion systems allows UAVs to contribute a reduction in greenhouse gas emissions in urban areas [42, 54]. Moreover, the more direct flight paths of UAVs could enhance energy efficiency, even when restrictive urban flight policies are applied [55]. Additionally, some recent innovation in UAVs technology, such as the use of lightweight materials and improved battery technology [56] or more efficient battery management [57–59] can lead to an additional increase in their energy efficiency, thus allowing a more sustainable performance [60,61].

2.3. Autonomous delivery robot (ADR)

The integration of ADRs into SLML presents a solution for addressing the twin challenges of emissions and energy consumption within the logistics sector. A recent study [62] highlights the effectiveness of ADRs in achieving this goal. Beyond environmental benefits, ADRs offer significant cost advantages over traditional delivery methods. Hoffmann and Prause [63] report that ADRs can achieve unit delivery costs up to 15 times lower than the normal price for last mile deliveries with ICEV in high-salary level economies. This economic benefit is corroborated by Garus et al. [64], who found that ADRs deliver a higher return on investment (ROI) compared to older Euro 4 diesel vans (41 % ROI difference). While the ROI benefit diminishes against Euro 6 diesel vans, ADRs still offer a competitive solution. However, a key limitation of ADRs lies in their speed compared to traditional delivery methods.

While UAVs can achieve faster speeds due to their ability to fly, ADRs can still offer competitive delivery times. According to Alverhed et al. [65], ADRs can potentially achieve significant savings in travel time, especially when handling multiple orders with the same ADR.

Some researchers, to solve the limitation regarding the inability to deliver more than one package in a trip, proposed integrating ADRs with other technologies to create a more comprehensive SLML solution: one promising approach involves combining ADRs with E-vans. Thus, a recent study [66] outlined a greenhouse gas reduction of 61 % when ADRs are deployed in conjunction with EVs, and a staggering 94 % reduction when solely using ADRs. Alfandari et al. [67] further emphasize this potential through simulations. Their research suggests that strategically routing ICEVs to launch and collect ADRs can significantly decrease carbon equivalent emissions. This integration could contribute to improve the intrinsic greener performance of ADRs, but also to increase simultaneously the range and speed of ICEVs and ADRs.

An additional consideration for ADR implementation involves their potential synergy with ICEVs. Boysen et al. [68] and Simoni et al. [69] explored the possibility of combining ADRs with ICEV delivery systems. This hybrid approach allows ADRs to leverage ICEVs for faster travel to distant locations, ultimately preserving battery life and reducing refuelling costs. Ostermeier et al. [15] found that under specific conditions, such hybrid solutions can be both cost-effective (up to 68 % reduction compared to standalone ICEV delivery) and environmentally friendly due to reduced emissions. However, the environmental benefit of this approach depends on the emissions standard of the ICEV being used.

Beyond these considerations, the successful implementation of ADRs necessitates addressing broader infrastructure and clear regulations governing the interaction between ADRs and pedestrians [70]. To encourage ADRs' adoption by users, it is essential to tailor communication strategies that promote a favourable perception of them. This involves highlighting their advantages, as outlined by Yuen et al. [71], including their perceived sustainability as a convenient last mile delivery option and their user-friendly nature for receiving deliveries.

3. The proposed decision support tool

While prior research has often examined individual delivery modes—such as UAVs or E-vans—in isolation or within specific contexts, few contributions offer a comparative, scenario-driven framework that accounts for varying operational conditions. Unlike existing studies that typically assess either economic or environmental dimensions, this work integrates both aspects through standardized KPIs and a simulation-based decision support tool adaptable to multiple delivery systems, with the aim of supporting more informed strategic decisions.

In detail, the objective of the proposed model is to assess, under specific operational conditions, the performance of innovative as well as smart LML delivery systems - such as UAVs, ICEVs, E-vans, and ADRs- by evaluating based on a set of key performance indicators (KPIs), integrating economic and environmental impacts. Thus, the proposed tool allows to carry out scenario analysis, by evaluating uncertainty based on most critical variables – such as customer daily demand and traffic conditions – that could affect the overall performance of such a delivery system.

The tool is flexible and can be applied to any urban context by adding geographic data (e.g. pick up locations, streets, etc.) and LML service information.

First of all, there are two types of input parameters in the proposed model:

- Urban scenario dependent variables: they consist of information that characterize the specific LML service in analysis; they are the daily demand and the level of traffic in the specific urban area. These variables could be uncertain, allowing a more realistic representation of operational environments.
- LML delivery service parameters: they do not vary according to the specific urban localization, but they depend on the specific technology adopted for LML service; thus, they are constant for each evaluated scenario. The main parameters are vehicle performance, loading capacity, loading and unloading time, and ones defined specifically for unmanned delivery systems, such as order preparation time, delivery maximum distance and payload capacity.

The main outputs provided by the proposed model regards:

- Fleets Composition: based on demand and available resources, the model estimates the total number of resources that are required for completing the delivery service with traditional and smart LML technologies.
- Impact Analysis: based on the specific KPI evaluations, environmental an economic performance of each LML service under each defined scenario can be evaluated allowing to compare them in a holistic way.

The proposed model is composed by different modules, which are depicted in Fig. 1, and described as follows:

a. *Delivery Routing Definition Module*: after acquiring data about the urban delivery scenario, a routing optimization process is performed trough a module developed in Python (i.e., OpenRouteService API). This module generates the most efficient delivery routes by considering factors like vehicle type and geographical constraints. This module works only for ICEV and E-vans technology.
b. *The Simulation Module*: The core of the tool uses a hybrid simulation approach combining Agent-Based Simulation (ABS) and Discrete Event Simulation (DES); the adopted software is Anylogic. The simulation model allows to define the fleet composition and provides final information about the LML services, such as actual duration of a delivery service, travelled kilometres, etc.
c. *The Scenario Analysis Module*: The outputs from the simulation model are provided to this module aiming to estimate quantitative values for the proposed set of KPIs, which include total cost, energy consumption, and actual emissions levels under each urban scenarios and for each LML delivery service based on smart and/or traditional technologies.

As defined previously, based on geographical input data, the first analysis that the tool carries out is to define an optimal route for ICEV or E-vans delivery. Thus, acquiring data about urban scenario (cartography, pick up pint locations, etc.), the module allows to define an optimized routing based on these data input. An example is depicted in Fig. 2.

Results – i.e. optimized routings- are provided to the simulation module, as shown in Fig. 1, in order to evaluate the final fleet composition and data about each analysed LML delivery service. The basic logic of the proposed simulation module is reported in Fig. 3 outlining interactions between DES and Agent based approaches.

Fig. 4, 5, 6, 7

Results regarding the actual development of the delivery service are then provided to the scenario analysis module to evaluate KPIs from an economic as well as environmental point of view for each analysed delivery system. Information provided regards, for example, the total estimated number of batteries required to fulfil the delivery service, the total average delivery time as well as the total travelled distance for each analysed LML delivery system.

In detail, a set of specific KPIs has been introduced in the module to evaluate the economic and environmental performance of each LML, as reported in Table 1. First of all, it has to be noted that the index “k” in the formulas indicates the specific delivery service scenario that is evaluated. They refer to traditional and smart technologies evaluated for the LML service.

The quantitative calculation of each proposed KPI is detailed as follows.

The Delivery Rate (DR_k) is calculated as the ratio between the total number of parcels delivered in a day (dd) defined as parcel delivered per day, divided by the total time required to complete all deliveries (T_k) estimated over the total length of the simulation, which is the total estimated working period (e.g., 300 days in a year).

$$DR_k = \frac{\mathrm{dd} * 300}{T_k} \qquad \begin{matrix} \forall\, dd \\ \forall\, k \\ \forall\, traffic\ conditions \end{matrix} \tag{1}$$

The second KPI is introduced in equation (2) and refers to the total costs $\left(TC_k^{dd}\right)$ to deliver dd parcels for 300 days in four scenarios. It includes investment costs $\left(\mathrm{I}_k^{dd}\right)$, maintenance expenses $\left(\mathrm{M}_k^{dd}\right)$, operating costs $\left(\mathrm{O}_k^{dd}\right)$, and energy cost $\left(\mathrm{E}_k^{dd}\right)$. We consider investment cost as annual amortization, and other costs as yearly expenses.

$$\mathrm{TC}_k^{dd} = \mathrm{I}_k^{dd} + \mathrm{M}_k^{dd} + \mathrm{O}_k^{dd} + \mathrm{E}_k^{dd} \qquad \begin{matrix} \forall\, dd \\ \forall\, k \\ \forall\, traffic\ conditions \end{matrix} \tag{2}$$

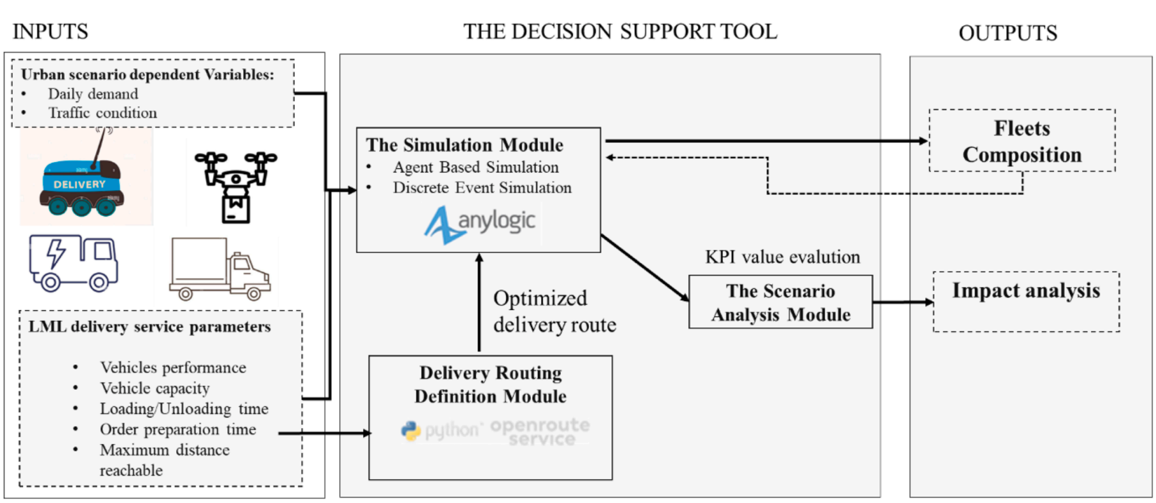

Fig. 1. Information flows and interactions in the proposed Model.

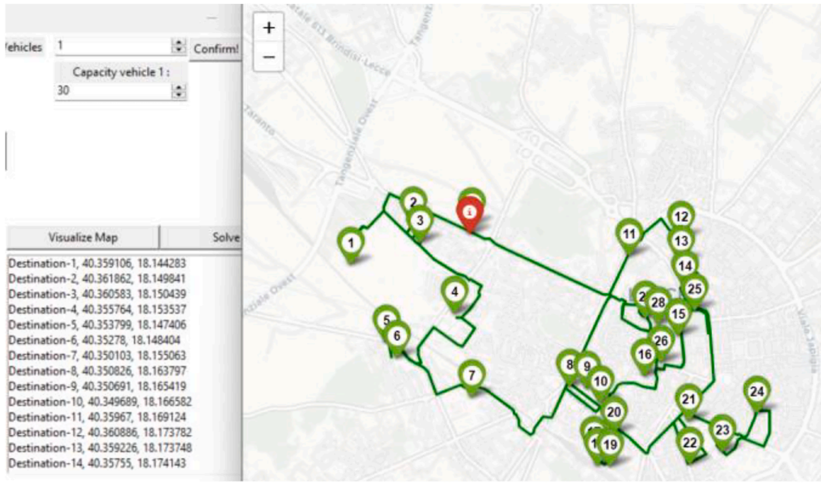

Fig. 2. Example of data visualization provided by the proposed Delivery Routing Definition module.

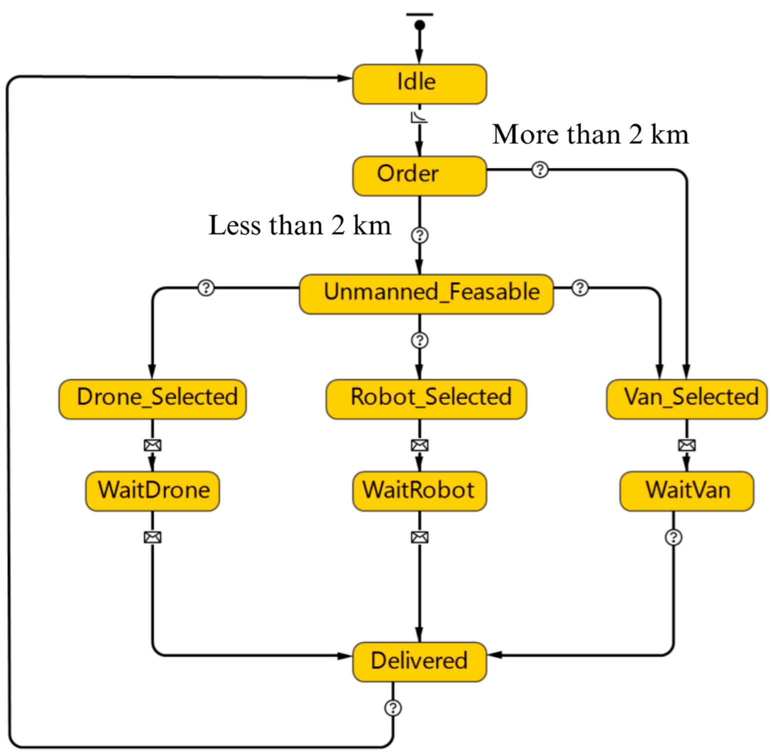

Fig. 3. Example of logic applied in the simulation module.

In detail, the investment costs (reported in Eq. (3)) are determined by the acquisition cost ($\mathrm{cv_k}$) of the vehicles calculated in fleet composition, reported as annual depreciation of initial investment. With unmanned vehicles, this includes the number of batteries and chargers ($\mathrm{bb_k}$) needed to meet the daily demand and their cost ($\mathrm{cbb_k}$).

$$\mathrm{I_k^{dd}} = \mathrm{cv}_k + \alpha * (\mathrm{bb}_k * \mathrm{cbb}_k) \qquad \begin{array}{c} \forall\, dd \\ \forall\, k \\ \forall\, traffic\ conditions \end{array} \tag{3}$$

Where α is a coefficient associated to the scenarios involving the acquisition of further batteries and chargers, so its value is 1 in case of unmanned delivery, zero otherwise.

The total cost of maintenance (4) is determined by multiplying the average cost per kilometre of interventions (cm), which is then multiplied by the total kilometres travelled by each vehicle in a year.

$$\mathrm{M_k^{dd}} = \mathrm{cm} * \mathrm{km_k^{dd}} \qquad \begin{array}{c} \forall\, dd \\ \forall\, k \\ \forall\, traffic\ conditions \end{array} \tag{4}$$

Operational expenses (5) are related to annual salaries for operators ($\mathrm{s_k}$), vehicle ownership taxes (pf_k) and insurance ($\mathrm{ins_k}$). For annual salaries operators, the difference occurs only in scenarios 3 and 4 (unmanned deliveries). In this case there are two types of compensation to be considered: an operator responsible for loading and unloading, and controlling the vehicle condition, and an operator who controls the vehicle during delivery.

$$O_k = \mathrm{s}_k + \mathrm{ins}_k + pf_k \qquad \begin{array}{c} \forall\, dd \\ \forall\, k \\ \forall\, traffic\ conditions \end{array} \tag{5}$$

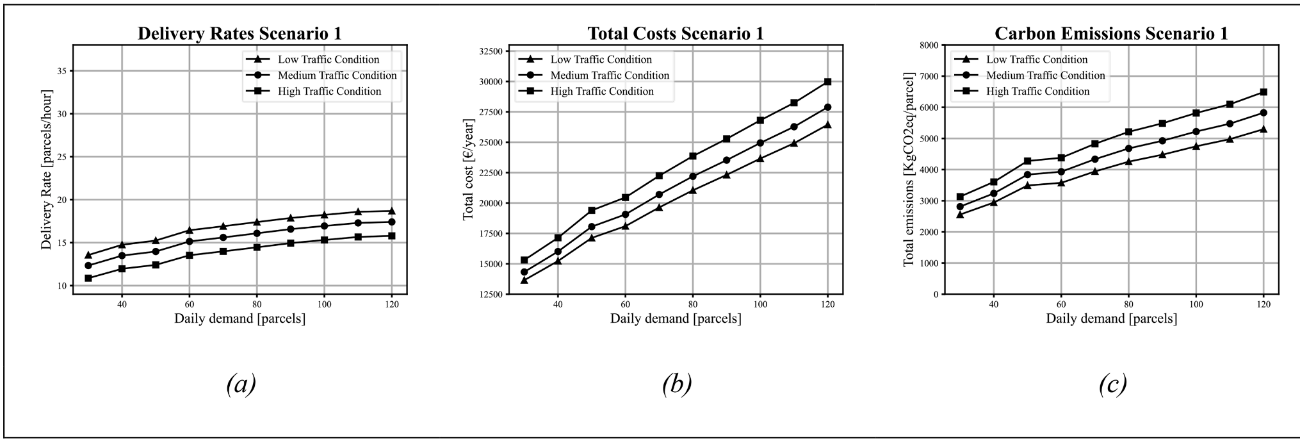

Fig. 4. Trend of KPIs in scenario 1: (a) delivery rate (DR_k), (b) total costs $\left(TC_k^{dd}\right)$, and (c) CO_{2eq} emissions $\left(TE_k^{dd}\right)$.

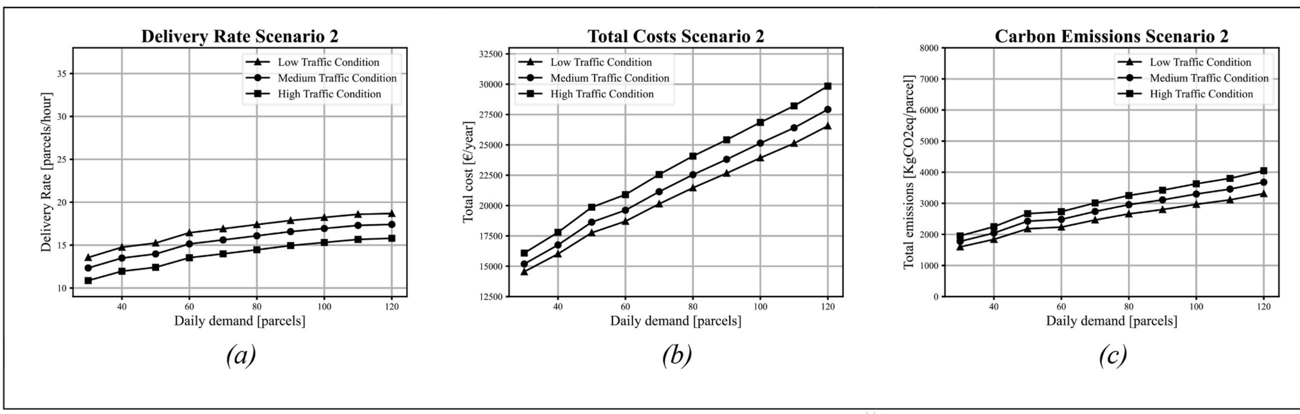

Fig. 5. Trend of KPIs in scenario 2: (a) delivery rate (DR_k), (b) total costs $\left(TC_k^{dd}\right)$, and (c) CO_{2eq} emissions $\left(TE_k^{dd}\right)$.

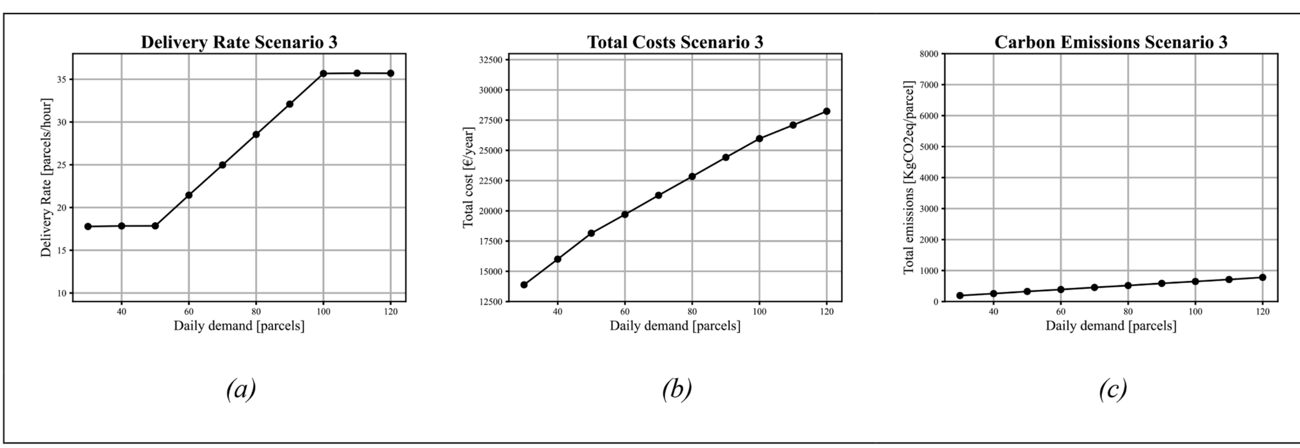

Fig. 6. Estimated KPI values for Scenario 3: (a) delivery rate, (b) total costs, and (c) CO_{2eq} emissions.

Energy costs (6) are related to the energy used in the scenario to satisfy the delivery demand. They are calculated considering the specific consumption of vehicle k (cons_k) multiplied by the energy cost (ec_k) and the distance covered km_k^{dd}.

$$E_k^{dd} = \text{cons}_k * ec_k * \text{km}_k^{dd} \qquad \begin{array}{c} \forall\, dd \\ \forall\, k \\ \forall\, \textit{traffic conditions} \end{array} \tag{6}$$

Finally, the last KPI is the one relating to CO_{2eq} emissions. The estimation of the carbon equivalent emissions generated by each delivery system refers exclusively to those related to the last mile deliveries, which are considered following the guidelines of the Global Logistics Emissions Council (GLEC) emission framework [72]. The GLEC protocol covers emissions from the use of fuels usage. However, as regards electric vehicles, only the emissions due to the production of electricity to recharge the batteries are considered. According to Eq. (7), emissions are calculated by multiplying the vehicles consumption in the four scenarios by the fuel emission factor or the electricity production

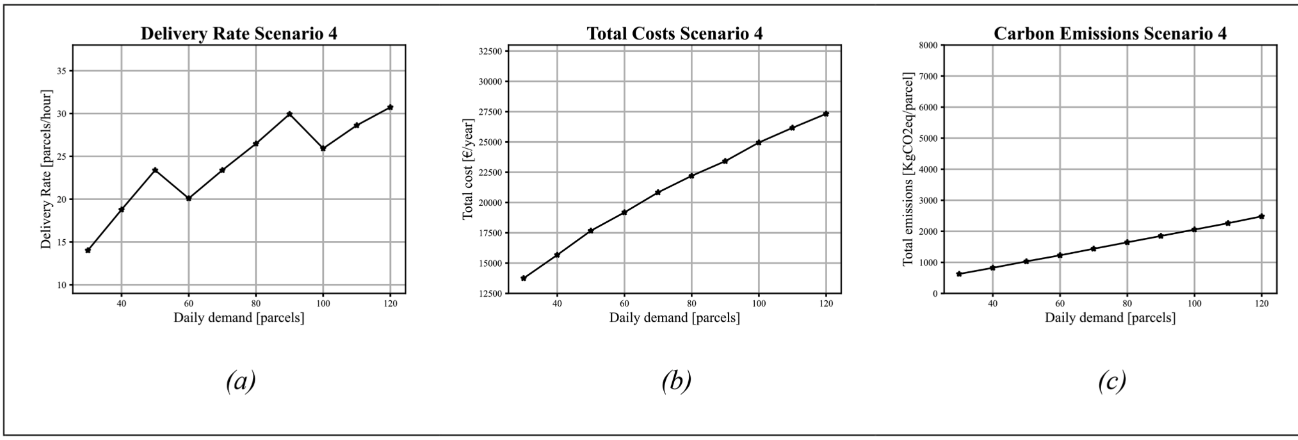

Fig. 7. Estimated KPI values for scenario 4: (a) delivery rate, (b) total costs, and (c) CO_{2eq} emissions.

Table 1
Key performance indicators introduced to evaluate scenarios performances.

Technical-Economic KPIs		
Estimated Delivery rate in scenario k using previously defined fleet compositions	$\boldsymbol{DR_k}$	$\left[\frac{\text{parcels}}{\text{h}}\right]$
Estimated Total costs in scenario k using previously defined fleet compositions	$\boldsymbol{TC_k}$	[€]
Environmental KPI		
Estimated Total carbon equivalent emissions in scenario k using previously defined fleet compositions	$\boldsymbol{TE_k}$	[$kgCo_2eq$]

emission factor (Ef_k).

$$\mathrm{TE}_k^{dd} = \mathrm{km}_k^{dd} * \mathrm{cons}_k * \mathrm{E}f_k \qquad \begin{matrix} \forall\, dd \\ \forall\, k \\ \forall\, traffic\ conditions \end{matrix} \tag{7}$$

3.1. Experiment setup and scenario definition

The scenario analysis carried out in this study aims at comparing the performance of different LML delivery systems under varying conditions, such as customer demand and traffic levels. The proposed model has been tested in a real urban context – the city of Lecce, located in southern Italy - to evaluate the feasibility and effectiveness of the proposed tool in assessing the performance of different LML delivery systems under realistic conditions. The urban area in analysis is a small town, with an urban restricted zone, and with a time-dependent traffic level: central hours are usually considered as rush hours.

The experiments are designed to evaluate the performance of these scenarios by simulating deliveries in this urban area of Lecce. The simulation length is set to 300 working days with 8 working hours per day to ensure a comprehensive evaluation under realistic conditions. The goal is to capture the interplay between delivery systems and key operational variables, including customer demand, traffic levels, and system-specific parameters.

First of all, four scenarios are defined based on LML delivery system type, outlined by the k index. These scenarios are:

- **Scenario 1** ($k = 1$): Delivery using ICEVs.
- **Scenario 2** ($k = 2$): Delivery using E-vans.
- **Scenario 3** ($k = 3$): Delivery using UAVs.
- **Scenario 4** ($k = 4$): Delivery using ADRs.

The purpose is to compare these different delivery systems in a holistic way, from economic and environmental points of view. The comparison has been developed by varying daily customer demand and traffic level aiming to evaluate overall performance of each delivery system in different operational conditions. It has to be noted that traffic level influences only the performance of Scenarios 1 and 2.

Urban scenario dependent variables are defined as follows:

- Daily demand (dd) has been defined as a set of discrete values ranging from 30 to 120 parcels/day, with increments of 10. These levels were selected to cover a representative range of deliveries for a small city context, from lower to higher demand, allowing for a comprehensive evaluation of the system's performance across different workload conditions.
- Traffic Condition: traffic conditions have been defined considering the characteristics of a small city, approximating traffic into three discrete levels (low, medium, and high) to reach a reasonable simplification for modelling delivery operations. The following levels of traffic conditions have been assumed for scenarios 1 and 2:
  - Low traffic conditions, representing smooth traffic flow typically observed during off-peak hours. In this condition, we assume an average vehicle speed of 30 km/h, while vehicle consumption efficiency ($cons_k$) is at its best due to minimal stop-and-go cycles and steady driving patterns.
  - Medium traffic conditions, corresponding to moderate congestion, such as during periods of regular daily activity. Here, the average speed considered is 25 km/h and $cons_k$worsens due to more frequent accelerations and decelerations, leading to increased energy consumption.
  - High traffic conditions, reflecting peak-hour traffic, where increased vehicle density may lead to slower deliveries. Under these conditions, we assume an average speed of 20 km/h, while $cons_k$ reaches its worst levels as prolonged idling, frequent braking, and acceleration spikes result in significantly higher fuel or energy consumption.

Estimated values for other input parameters are reported as follows:

- Vehicle transportation capacity $\left(\text{defined as Capacity}_k\right)$: it has been assumed equal to 150 parcels in scenario 1 and 2; and equal to 1 parcel for other scenarios.
- Loading/Unloading time $(\text{defined as LU time}_k)$: $\text{LU time}_{1,2} = 2\ \text{min}$; $\text{LU time}_{3,4} = 5\text{min}$
- Average vehicle speed in scenario k (Speed_k):
  - $\text{Speed}_3 = 72\,\frac{\text{km}}{\text{h}}$ [73]
  - $\text{Speed}_4 = 6\,\frac{\text{km}}{\text{h}}$ [74]

In addition, there are a group of parameters used only in scenario 3 and 4 that are reported as follows:

- Average time for loading, secure the box and check its status (defined as Preparation Time_k):
  - Preparation $\text{Time}_{3,4} = 10$ min
- Maximum allowable distance for delivery (defined as range_k) :
  - $\text{range}_3 = 8$ km [73]
  - $\text{range}_4 = 2.5$ km [74]
- Vertical speed in scenario 3 $= 18 \frac{\text{km}}{\text{h}}$ [73]

4. Results analysis

The analysis of results focuses on evaluating the performance of different LML delivery systems under varying operational conditions, as defined in the methodology. The outcomes are presented in terms of fleet composition and KPIs for each scenario, providing insights into the economic and environmental trade-offs of each system.

4.1. Definition of fleets composition

The first set of results concerns the fleet size design, calculated through the simulation module. Table 1 presents the estimated fleet composition under different daily demand levels for all delivery service types. The findings highlight the substantial number of resources required for unmanned delivery services, particularly UAVs and ADRs, due to their operational constraints. UAVs, despite their high speed, are limited by their single-parcel delivery capacity, requiring multiple flights to meet increasing demand. However, their rapid transit times enable a high turnover rate, which prevents a proportional increase in fleet size as demand grows. In fact, while the daily demand increases fourfold from 30 to 120 parcels/day, the required UAV fleet size increases only by 100 % (from 5 to 10 vehicles). Similarly, ADRs, despite their much lower speed, exhibit a fleet size growth of only 100 % (from 15 to 30 vehicles), demonstrating that their ability to operate in parallel and their optimized resource utilization can mitigate the expected proportional increase. On the other side, ground-based delivery systems (ICEV and E-van), operating at speeds dictated by traffic conditions, require only a single vehicle for all levels of demand and traffic conditions. This result is influenced by the fact that, within the considered range, vehicle capacity is not fully saturated, and delivery schedules remain within feasible operational limits. As a result, their fleet size remains constant despite the fourfold increase in demand and the varying traffic conditions. These observations confirm that the relationship between delivery demand, fleet size, and vehicle speed is highly non-linear, as different transport modes scale differently based on their operational constraints and efficiency in parallel task execution.

Table 2

4.2. KPI analysis for each scenario

A comparison for each specific delivery system has been carried out under different daily demand and traffic conditions by estimating the three KPIs defined in Section 3.

The analysis of Scenario 1 highlights that despite a 33.33 % speed reduction from low traffic (30 km/h) to high traffic (20 km/h), KPIs are not proportionally affected due to route optimization and delivery consolidation.

The Delivery Rate increases with demand, reaching +37.82 % under low traffic, +41.14 % under medium traffic, and +45.36 % under high traffic as demand rises from 30 to 120 parcels/day. Interestingly, the increase is slightly higher under high traffic, suggesting that at higher demand levels, vehicle capacity is better utilized, mitigating congestion effects. However, comparing low to high traffic, the Delivery Rate decreases from 24.77 % at 30 parcels/day to 18.30 % at 120 parcels/day, showing that congestion impact diminishes as demand increases. This suggests that higher demand causes shorter travel distances between stops, and better vehicle load utilization, leading to fewer empty or underutilized trips, making the system more resilient to speed reductions. Total Costs rise by 94–95 % as demand grows from 30 to 120 parcels/day, with a consistent 11–12 % increase between low and high traffic levels, indicating that fuel and labour expenses are influenced by demand level more heavily than by traffic conditions. Carbon emissions increase by 107.17 % when demand quadruples, indicating a strong correlation with total mileage rather than with traffic conditions. In contrast, emissions rise by only 18.37 % as traffic conditions worsen, suggesting that congestion has a relatively lower impact on overall emissions compared to delivery volume.

In Scenario 2, considerations over Delivery rate are similar to Scenario 1. Analysing Total Cost there is a significant cost increase with demand, reaching +82.58 % under low traffic, +83.84 % under medium traffic, and +85.51 % under high traffic as deliveries rise from 30 to 120 parcels/day. The cost growth trend closely follows that of ICEVs, indicating that energy consumption scales similarly with delivery volume despite the efficiency advantages of electric propulsion.

However, when comparing costs between low and high traffic at fixed demand levels, the increase is between +9.56 % and +10.99 %, slightly lower than that observed for ICEVs: this is due to E-VANs electric engine efficiency; total cost value is also similar to scenario 1, but fluctuations in energy and fuel price can affect this evaluation. Carbon emissions increase by 107.17 % across all traffic conditions as daily demand grows from 30 to 120 parcels/day, mirroring the trend observed for ICEVs, even if from scenario 1 to scenario 2 there is a 37.65 % carbon emission reduction. However, emissions increase due to traffic congestion remain constant at about +18 % across all demand levels. This highlights a key distinction: unlike ICEVs, where fuel inefficiencies cause emissions to rise significantly with traffic, E-VAN emissions are linked primarily to energy production rather than traffic conditions.

In Scenario 3, unlike terrestrial vehicles, UAVs can travel directly between the delivery point and the depot, significantly reducing travel times. The Delivery Rate increases by +100.8 % as daily demand rises from 30 to 120 parcels/day. This increase is higher than what is observed for scenario 1 and scenario 2, likely because for higher demand levels the number of UAVs increases, unlike ICEVs and E-VANS. Total costs increase by +103.37 %, indicating a near-linear cost growth as more UAVs are deployed to meet the demand. The cost increase is mainly due to battery energy consumption, drone maintenance, and fleet expansion, as each additional UAV requires independent operations. Unlike terrestrial vehicles that consolidate multiple parcels per trip, UAVs handle one delivery at a time, making cost efficiency a challenge at higher demand levels. Carbon emissions increase with demand, following a steeper trend compared to terrestrial vehicles. This is due to the 100 % increase in the number of UAVs used, which results in a 302.53 % rise in emissions when scaling from 30 to 120 packages delivered per day. However, on average, UAV emissions are 89 % lower

Table 2
Estimated fleet compositions for each daily demand analysed level (and different traffic conditions in scenarios 1 and 2).

Fleet composition	Daily demand									
	30	40	50	60	70	80	90	100	110	120
Required ICEV total number	1	1	1	1	1	1	1	1	1	1
Required of E-van total number	1	1	1	1	1	1	1	1	1	1
Required of UAV total number	5	5	5	6	7	8	9	10	10	10
Required of ADR total number	15	20	20	20	24	27	27	30	30	30

than ICEVs and 82.60 % lower than E-VANs, reflecting their reduced reliance on fossil fuels and greater energy efficiency per trip. Despite this advantage, their scalability in terms of sustainability remains a point to investigate, as increased demand necessitates more frequent recharges and greater electricity consumption, potentially offsetting their environmental benefits.

In Scenario 4, Delivery Rate increases by +119.05 %, with a similar trend seen in the UAV scenario. This suggests that ADR performance scales more effectively than UAVs with fleet expansion. Unlike UAVs, which face energy limitations due to battery constraints, ADRs benefit from a continuous operational cycle, allowing them to efficiently handle more deliveries when more units are deployed. The drops observed in the Delivery Rate at 60 and 100 parcels/day are due to an increase in the total time required to complete deliveries, caused by a high saturation of resources. While the number of ADRs is sufficient to meet demand, the units are operating at full capacity, leading to longer cycle times and reduced efficiency. Additionally, a threshold effect in resource allocation occurs, as ADRs are added in discrete blocks. At certain intervals, the number of available units may be just enough to meet demand but not sufficient to reduce delivery time significantly. Total costs increase by 98.69 %, meaning that cost efficiency improves slightly as fleet size doubles. However, since ADRs must follow terrestrial path, their delivery efficiency remains constrained compared to aerial solutions. Carbon emissions increase by 295.54 % with the demand, significantly more than any other delivery system analysed. This sharp rise is likely due to the compounded energy consumption of multiple ADRs operating simultaneously, as well as the longer delivery times caused by their slow speed. Unlike UAVs, which reach their destinations quickly and return to base, ADRs spend more time per delivery, increasing energy consumption for extended periods. Analysing the value of the emissions we have that ADR can reduce the total emissions per parcel by 65.11 % compared to ICEV, and 44.75 % compared with E-van, but it worsens by a −217.63 % when compared with UAVs emissions.

Overall, results show that in the case study unmanned vehicles can guarantee higher delivery rates than ICEVs and E-VANS on average, while also entailing similar total costs and guaranteeing sensitively lower carbon emissions, especially in the UAV scenario.

5. Discussion

The proposed decision support tool has been validated with a simulation demonstrating its effectiveness in comparing different last-mile delivery systems holistically, from both an economic and environmental perspective. The tool enables a structured evaluation of traditional and innovative delivery methods, providing insights into their performance under different demand levels. It allows for scenario analysis, helping stakeholders assess trade-offs between cost efficiency, operational constraints, and environmental impact.

Answering to first research question (RQ1), the proposed tool enables a structured comparison of LML systems by integrating economic and environmental indicators into a single decision-making framework. Through scenario modelling, the tool highlights how different delivery systems scale with demand, revealing key trade-offs between cost, efficiency, and emissions. The simulation results confirm that UAVs and ADRs provide significant environmental benefits due to low operational emissions. However, in low-traffic scenarios, the total cost values for ICEVs and E-VANs (Scenarios 1 and 2) are slightly lower than those observed for UAVs and ADRs (Scenarios 3 and 4). As traffic congestion increases, the total cost KPI for all delivery systems converges, indicating that traffic-related inefficiencies in traditional vehicles offset their initial cost advantage. This highlights the need for demand-specific optimization when integrating new technologies into urban logistics, ensuring that cost-effectiveness and environmental benefits are balanced depending on traffic conditions and delivery requirements.

About the second research question (RQ2), the tool facilitates a systematic comparison of different delivery technologies, highlighting strengths, weaknesses, and trade-offs. Traditional ICEVs, while still benefiting from established infrastructure, are affected by high fuel costs and emissions, making them less sustainable in long-term urban logistics. E-VANs emerge as a practical alternative, offering similar costs to ICEV but reduced emissions. UAVs and ADRs, while minimizing operational emissions, might present scalability and cost challenges, as fleet expansion is required to meet growing demand, even if results show that as traffic condition worsen (in scenario 1 e 2), ADRs and UAVs have similar total cost values compared to ICEV and E-Van deliveries. The tool underscores how different delivery systems respond to various levels of demand, aiding decision-makers in evaluating the feasibility of integrating new solutions.

The findings offer practical and theoretical implications for policymakers, logistics providers, and researchers:

- Practical Implications: The tool provides a robust framework for evaluating the sustainability of LML strategies, enabling the development of policies that incentivize the adoption of greener technologies like E-vans and unmanned systems.
- Theoretical Implications: The insights derived from the simulation can help optimize fleet composition and routing strategies. For instance, while ADRs and UAVs reduce emissions, their operational constraints necessitate careful planning to ensure cost-effectiveness and timely deliveries. The tool can assist in identifying optimal fleet configurations and delivery strategies tailored to specific urban contexts.

Despite its strengths, the study is subject to several limitations. First, the simulation model do not account for all variables that could potentially impact LML services, such as extreme weather conditions or unexpected obstacles. The capabilities and limitations of unmanned systems, particularly UAVs, are based on current technological advancements, which are likely to evolve in the near future. Moreover, the environmental impact assessment focuses solely on operational emissions, and a more comprehensive analysis should include an evaluation on energy production source, or the full life cycle of delivery systems, covering production, maintenance, and disposal stages. Furthermore, the study does not explore the social implications of widespread adoption of unmanned systems, such as privacy concerns and noise pollution. All these aspects could be addressed in further research, with the aim of increasing the reliability of the proposed tool.

Nonetheless, the results emphasize the importance of a holistic approach to LML system design. Balancing cost, efficiency, and environmental impact remains a challenge, but the proposed tool provides a valuable resource for addressing these complexities. By enabling detailed scenario analysis and supporting informed decision-making, the tool contributes to the development of more sustainable urban logistics strategies, benefiting both stakeholders and the broader community.

6. Conclusion

This study presents a decision support tool for the design and assessment of LML systems based on traditional and innovative technologies (such as unmanned delivery services): the tool aims to design most critical elements of different LML delivery services (e.g., the fleet dimension) by evaluating economic and environmental impacts of these services. A set of quantitative KPIs has been defined in a standard way that fits all types of analysed delivery services in different operational conditions. A test case has been carried out to validate the proposed tool, providing insights grounded in experimental results. Specifically, the analysis considered four scenarios with different delivery modes (i.e., ICEVs, E-vans, UAVs and ADRs), and the outcomes show that unmanned delivery methods, particularly UAVs, can achieve higher delivery rates and significantly lower CO_{2eq} emissions compared to conventional terrestrial vehicles, especially in urban contexts with high demand and dense delivery points, while presenting similar levels of total cost. On the other hand, E-vans showed the best trade-off between cost and environmental impact among ground-based systems, especially when demand increased. These results emphasize the importance of integrating innovative technologies into LML strategies to optimize delivery operations and meet the growing customer demand while minimizing costs and environmental impacts.

Additionally, the potential of the tool to provide effective feedback has been highlighted, not only for researchers but also for decision-makers in the urban logistics field. For instance, the results indicated that larger fleet sizes are necessary for unmanned systems to maintain delivery efficiency, and fleet composition has a direct impact on total costs. Moreover, operational emissions were substantially lower for electric-powered systems, confirming their suitability for sustainable logistics. Such findings underline the importance of strategic decision-making that incorporates environmental and operational efficiency into the planning and implementation of LML systems. Stakeholders in the LML sector, including policymakers and logistics providers, should leverage tools like the one proposed in this study to optimize resource allocation, adopt innovative delivery methods, and achieve a balance between service quality, cost-effectiveness, and environmental sustainability.

Future research could address the limitations described in Section 5, exploring advanced optimization algorithms, tailored to innovative delivery technologies, to further enhance the efficiency and sustainability of LML systems. Additionally, improving data collection by incorporating real-world performance data, such as vehicle efficiency and customer behaviour, would enhance the accuracy of the tool and expand its applicability. Furthermore, integrating a full life cycle assessment of delivery systems, including production, maintenance, and disposal stages, would provide a more comprehensive evaluation of their environmental impacts.

CRediT authorship contribution statement

Maria Grazia Gnoni: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Lorenzo Rubrichi:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Fabiana Tornese:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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