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Truck-based drone delivery system: An economic and environmental assessment

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ABSTRACT

Innovative solutions for last-mile delivery have sparked great interest among consumers and logistics operators. The combination of new technologies with existing ones can lead to new possible last-mile delivery configurations, among which truck-drone joint delivery is one of the most promising. This paper evaluates the environmental and economic sustainability of a last-mile delivery solution involving electric trucks equipped with drones, and it provides a comparison with traditional logistics systems. The comparative life cycle assessment methodology is used to quantify the greenhouse gas emissions per parcel delivered. The total cost of ownership methodology is adopted for the economic analysis. Results suggest that the truck-drone alternative leads to significant emissions reductions, while its cost performance is primarily affected by the drone automation level.

1. Introduction

Last-mile logistics is developing fast, driven by the growth of B2C e-commerce (Lim et al., 2018). The advent of new technologies, especially automated solutions (Joerss et al., 2016), may enable the disruption of the industry. Innovations will allow logistics operators to meet new customers' requirements, especially regarding delivery speed and reliability. They will simultaneously reduce costs, which is particularly important due to the industry's low operating margins (Allen et al., 2018). Drones could be among the first innovative technologies to disrupt last-mile logistics, and they are expected to be employed locally, mostly in rural and suburban areas (Joerss et al., 2016). However, future adoption of large-scale drone delivery will be influenced by technology reliability, companies' business models, consumer acceptance, and regulation (Simoudis, 2020). Moreover, among barriers to adoption, social, political, and legal challenges are currently the most critical (Sah et al., 2021). The legal challenges, in particular, have historically been limitation factors for the adoption of automated vehicles (Hoffmann and Prause, 2018). In 2019, the European Union issued—through Regulation 2019/947 and Regulation 2019/945—new directions and guidelines specifically for drones. The new regulatory framework provides detailed requirements that drones and remote pilots must abide by (e.g., ensure that the drone equipment is in good conditions, keep the relevant air traffic service unit updated, discontinue a flight in case of emergency). Under these requirements, delivery drones are allowed to fly beyond the visual line of sight (BVLOS) of the remote pilot after a preliminary risk assessment. However, current technological and legal constraints prevent fully automated drones from performing delivery operations BVLOS. In this regard, the current artificial intelligence (AI) technology level may satisfy completely or partially the legal requirements (UNIO, 2020), allowing

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Table 1
Selected literature on environmental assessments in drone logistics.

Paper	Drones		Traditional ground-based vehicles		Notes
	Utilization emissions [gCO2e/ delivery]	Production/ disposal emissions [gCO2e/delivery]	Utilization emissions [gCO2e/ delivery]	Production/ disposal emissions [gCO2e/delivery]	
Figliozzi (2017)	160	160	NA	30	Drone delivery configuration: drones from fixed depots; one-to-one route for drones, while one-to-many routes for vans Type of drone: quadcopter Type of traditional ground vehicle: diesel delivery van Delivery scenario: NA LCA phases: from cradle to grave
Stolaroff et al. (2018)	1264* 645** *Value regarding "large" drone with maximum payload 8 kg **Value regarding "small" drone with maximum payload 0.5 kg		*Diesel:* 1015 *Electric*: 943		Drone delivery configuration: drones from fixed depots Type of drone: quadcopter and octocopter Type of traditional ground vehicle: electric and diesel vanDelivery scenario: urban (San Francisco, US) LCA phases: from cradle to grave (without considering drones production and recycling)
Park et al. (2018)	From 3.5 (urban)to 39 (rural)	–	*Diesel:*From 27 (urban)to 350 (rural) *Electric:*From 17 (urban)To 226 (rural)	–	Drone delivery configuration: drones from fixed depots (pizza restaurant since the authors analyzed a pizza delivery emissions) Type of drone: quadcopter Type of traditional ground vehicle: electric and diesel motorcycle Delivery scenario: urban (Yangcheon-gu, KR) and rural (Pyeongchang-gun, KR) LCA phases: use phase
Kirschstein (2020)	From 440* to 1300* **computed by the authors*	–	*Diesel*: From 89* to 600* *Electric*: From 66* to 530* **computed by the authors*	–	Drone delivery configuration: drones from fixed depots Type of drone: octocopter Type of traditional ground vehicle: diesel and electric vanDelivery scenario: urban (Berlin, DE) LCA phases: use phase
Yowtak et al., 2020	1950* **computed by the authors*	–	*Diesel*: 2200* *Electric*: 830* **computed by the authors*	–	Drone delivery configuration: drones from fixed depots Type of drone: octocopter Type of traditional ground vehicle: diesel delivery van Delivery scenario: urban (Ann Arbor, US), grocery delivery

the automation of some steps of drone delivery operations in the future.

Large companies such as Google, Deutsche Post DHL, UPS, and Amazon have already started small-scale experiments with drone delivery systems (Stolaroff et al., 2018). Due to drones' limited operating range, the end customer is not reached directly from local distribution centers, but the logistics network typically includes intermediate depots, which could be either mobile or fixed (Kirschstein, 2020). A mobile depot is typically a delivery van equipped with drones (Campbell et al., 2018), as in the truck-drone joint delivery test performed by UPS (UPS, 2017). DHL instead tested a drone delivery system with fixed depots. These depots enabled the automatic loading and unloading of parcels from the drones, and they acted as locker stations, allowing customers to collect and deposit parcels up to 2.2 kg directly at the drone delivery station (DHL, 2020).

While previous research efforts mainly focused on drones departing from fixed depots, this research aims to analyze a delivery system where drones are launched from delivery trucks, which act as mobile depots, and compare it against traditional ground-based delivery alternatives—both traditional diesel vans (DVs) and electric vans (EVs). Environmental sustainability will be assessed by performing a comparative life cycle assessment (LCA) analysis (ILCD, 2010), while economic sustainability will be investigated by applying the total cost of ownership (TCO) methodology.

The remainder of the paper is organized as follows: Section 2 discusses previous studies in drone last-mile logistics. Section 3 describes the delivery configurations under analysis, the system boundaries, the methods applied, and the data inventories for both the environmental and economic analyses. In Section 4, the results are presented together with the sensitivity analysis. Finally, Section 5 displays the conclusion with a critical discussion of the results obtained.

2. Literature review

Researchers' interests have been focused mainly on operational optimization issues, providing methods to find depot locations for drones (Aurambout et al., 2019) or routings for both trucks and drones (Campbell et al., 2018; Moshref-Javadi et al., 2020; Murray and Chu, 2015; Murray and Raj, 2020). The literature review in the present work instead discusses studies proposing environmental and economic assessments in drone last-mile logistics. The selected literature for the environmental assessments is collected in Table 1. It evidences (i) which type of emissions are considered in the studies (utilization and/or production and disposal emissions), (ii) which vehicles' emissions are compared (e.g., drones vs. DVs or EVs), (iii) gCO2e/delivery where available, and (iv) relevant notes about the papers.

Figliozzi (2017) assessed the environmental impact of drones departing from a fixed depot using an LCA from cradle to grave. The study—comparing drones and DVs—concluded that DVs are the most eco-friendly means of delivery considering the emissions per kilogram transported and per unit distance. Drones can lead to an emission reduction compared to vans only when each van performs fewer than 10 deliveries per route. Moreover, the author highlighted the relevance of production phase emissions to the overall delivery system's environmental footprint, particularly for drones due to the polluting disposal process of batteries. Similarly, Stolaroff et al. (2018) analyzed the life cycle environmental impact of a drone delivery system with multiple intermediate fixed local depots connecting a regional distribution center with the final customer. In this scenario, small drones—with 0.5 kg payloads—generally lead to a reduction of CO2e emissions per package delivered (about 600 gCO2e/delivery by drone compared to 1,000 gCO2e/delivery by electric truck and to 1200 gCO2e/delivery by DV). On the contrary, large drones—with 8 kg payloads—display higher emissions (about 1300 gCO2e/delivery) compared to EVs or DVs. The analysis considered emissions from battery and fuels production as well as fuels combustion and electricity production required for transportation. Differently from Figliozzi (2017), warehousing emissions were included, but emissions from production of the vehicles—except for the battery—were not considered. In the end, the authors highlighted the relevance of the emissions caused by the network of intermediate depots and the impact of the local grid's specific electricity-production emissions. Park et al. (2018) compared instead the emissions of a pizza-delivery system using motorcycles or drones, both traveling a one-to-one route, and focused on utilization emissions only. The study revealed that drones have the lowest global warming potential: a drone emits 3.5 gCO2e/delivery traveling 0.8 km in urban areas and 40 gCO2e/delivery traveling 8.83 km in rural areas. A similar conclusion has been obtained by Yowtak et al. (2020), who performed an LCA analysis of grocery deliveries, comparing traditional ground-based vehicles with drones departing directly from the grocery store. The analysis, considering a drone with a high mass payload (35 kg), was focused only on the utilization phase. The delivery system with drones displays lower emissions compared to DVs but higher emissions compared to EVs. Kirschstein (2020) provided a detailed analysis of drone energy consumption, considering all the phases of a drone's flight (i.e., takeoff, level flight, hovering, and landing). The study showed that drone delivery using fixed depots does not have an advantage in terms of energy consumption over a traditional truck-based delivery system in most scenarios, especially in densely populated areas. Drone energy consumption ranges from 440 to 1300 gCO2e/delivery, while DV and EV consumption ranges instead from 89 to 600 gCO2e/delivery and from 66 to 530 gCO2e/delivery, respectively, making vans the less polluting system in most of the scenarios analyzed.

Concerning economic sustainability, various papers have taken costs into account for the formulation of truck-drone routing optimization problems (Campbell et al., 2018; Chiang et al., 2019; Dorling et al., 2017). Moshref-Javadi and Winkenbach (2021), in their review of the literature, highlighted the lack of comprehensive cost analyses of drone last-mile delivery systems, identifying only one study that addressed drone delivery economic viability (Sudbury and Hutchinson, 2016). Sudbury and Hutchinson (2016) estimated \$0.33 per delivery without considering labor costs. A more detailed cost analysis was performed by Doole et al. (2020) considering both capital and operational expenditure. The authors considered several scenarios, leading to the cost for drone food delivery from restaurant to customer ranging from €0.4 to €2.51. The scenario analysis is needed since delivery drone technology is a novelty in the industry and both capital and operational costs are expected to fall once delivery drones gain a critical mass (Doole et al., 2020). Furthermore, Campbell et al. (2018) argued that truck-drone economic sustainability depends on drones' operative costs and that multiple drones per delivery truck further improve the system cost performance.

Overall, previous research efforts mainly focused on drones departing from fixed depots. This research aims to analyze a delivery system where drones are launched from delivery trucks, which act as mobile depots, and compare it against traditional ground-based delivery alternatives—both traditional DVs and EVs. Environmental sustainability will be assessed by performing a comparative LCA analysis (ILCD, 2010), while economic sustainability will be investigated by applying the TCO methodology.

3. Methods and data

A detailed understanding of the underlying logistics system is a necessary preliminary step to compute the life cycle emissions and costs of any delivery system. The vehicles routing model and its main assumptions are first described in Section 3.1. The outcome of the routing model is used for both the environmental and economic analyses. Afterward, the main methodological steps of the LCA and the TCO analyses are discussed separately.

3.1. Underlying logistics system

The vehicle routing model developed by Campbell et al. (2018) has been adopted to compute the number of daily deliveries performed and the distance covered by both trucks and drones. The model aims at finding the optimal swath that minimizes the total operative cost. The optimal swath *w*, computed using a continuous approximation technique, is the maximum distance perpendicular

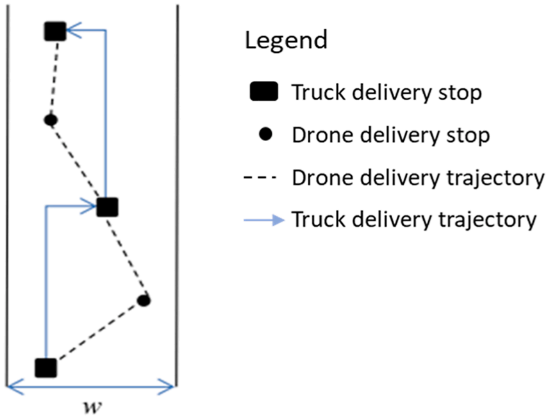

Fig. 1. Truck and drone trajectories (Campbell et al., 2018).

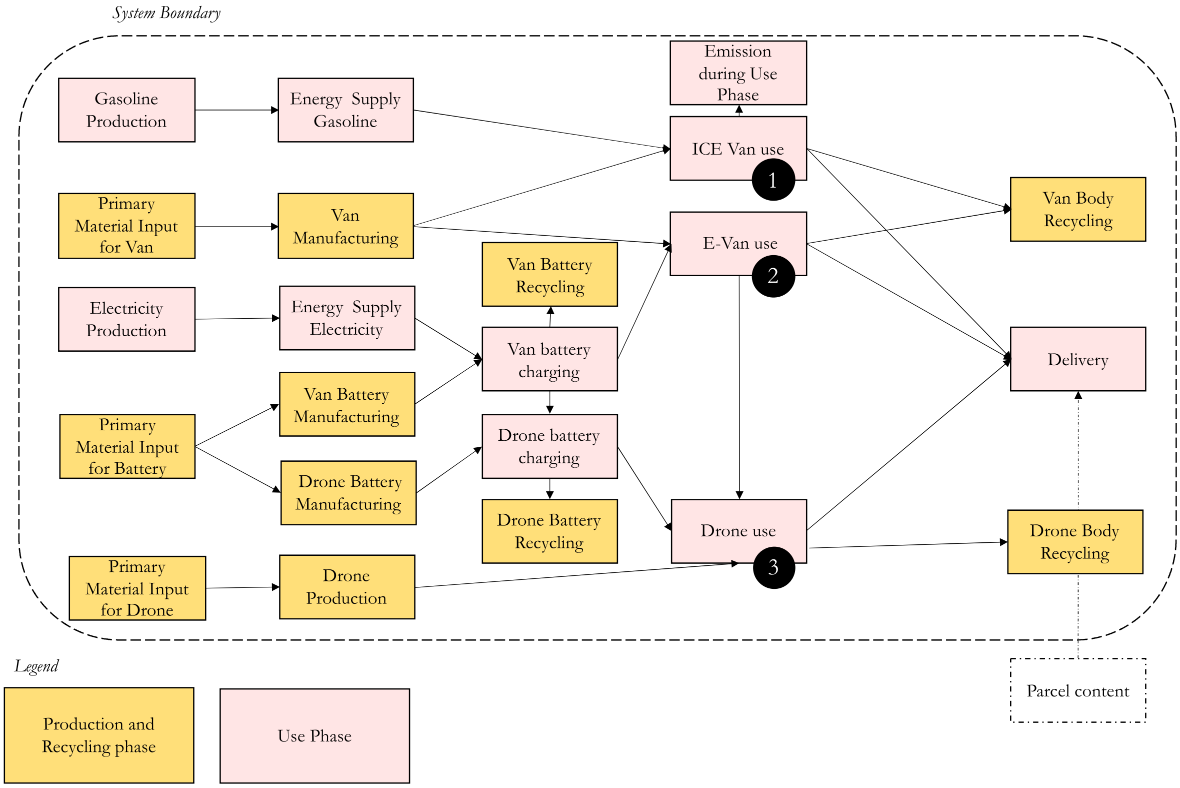

Fig. 2. LCA system boundaries.

to the truck trajectory that can be traveled by the truck to reach a destination. Fig. 1, taken from Campbell et al. (2018), shows a truck-drone delivery system with n, the ratio between the number of parcels delivered by drone and those delivered by truck, equal to 1. While Campbell et al. (2018) also considered systems with n greater than 1, and thus with multiple drones per each truck, this study assumes only one drone per truck, consistent with the current setup of the first real-life truck-drone delivery systems (UPS, 2017; Workhorse, 2020). Customers are distributed randomly in the delivery area, with a density δ. Truck and drone are assumed to perform deliveries in parallel—in particular the truck follows the L-shape trajectory displayed in Fig. 1, while the drone's trajectory follows a straight line between the starting point and destination. Appendix A displays the formulas obtained from Campbell et al. (2018) as well as the input parameters' description and values.

The key assumptions for the analysis are the following:

- The delivery service by both truck and drone has 300 working days per year, with one daily shift lasting 7.5 h.

- Every parcel weighs 2.5 kg, which covers up to 86% of the products delivered by Amazon (Amazon, 2019).
- All deliveries can be performed either by truck or by drone.
- Each destination corresponds to one delivery.
- A drone can only be launched and retrieved at two consecutive truck delivery stops (Campbell et al., 2018).
- Delivery time windows are not considered.
- For the internal combustion engine truck, no refueling time is considered.
- The marginal fixed time for a delivery with truck is set to 180 s.
- Hovering time is set to 30 s, as in Xu (2017). Hovering time is defined as the time spent by the drone remaining stationary in the air before landing at the customer destination. Eventually, the drone can also hover while waiting for the truck, but this is defined as *drone waiting time*, which is discussed in Section 3.2.3.1. For the electric truck, one hour of battery fast-charging time is considered when the amount of daily energy required under that specific scenario is larger than the truck battery capacity.
- The delivery speed is constant (Campbell et al., 2018).
- Vehicle trajectory is modeled according to Campbell et al. (2018)—see Fig. 1.
- A drone trajectory follows a straight line from origin to destination, as in Campbell et al. (2018) and Kirschstein (2020).

3.2. Life cycle assessment

After defining the goal and scope of the LCA (Section 3.2.1), each phase accounted for in the assessment will be discussed. In the end (Section 3.2.4), the methodology for the emissions' allocation to the functional unit will be explained.

3.2.1. Goal and scope

The comparative LCA methodology was used to compare the performance of the truck-drone joint delivery system with a traditional truck delivery system. The former system employed electric trucks, while the latter relied on both internal combustion engine and electric tucks. The LCA reference unit was the single delivered package, as in Stolaroff et al. (2018). The LCA system boundary was a "cradle to grave," covering the whole life cycle of the assets used in the distribution system (ILCD, 2010).

The elements included in the LCA, ranging from the input of raw materials to the assets' recycling phase, are represented graphically for the three alternatives under analysis in Fig. 2. In particular, Fig. 2 highlights the two main sections of the analysis: the production and recycling phase and the use phase. The unit processes were assessed in terms of their global warming potential, measured with the amount of greenhouse gas emissions—more specifically kg of carbon dioxide equivalent (CO2e). The LCA inventory included (i) secondary data; (ii) primary data from an interview conducted with one of the main Italian producers of drones, which provided information about the drone's technical specifications, costs and performances; (iii) the outcome of quantitative models such as the routing model (in Section 3.1 and Appendix A) and the energy consumption model for trucks and drones (in Section 3.3.3). All data sources are disclosed, and the variables subjected to the sensitivity analysis are listed and explained.

3.2.2. Production and recycling phase

To compute the emissions caused by the production phase, we adopted the models of Yang et al. (2018) and Figliozzi (2017). Regarding the emissions caused by the truck body, Yang et al. (2018) estimated them as:

$$CO2e_{truck} = e_{truck} \cdot m_{bodytruck} \tag{1}$$

where e_{truck} is the emission coefficient for truck body parts [kg CO2e/kg] and $m_{body\ truck}$ is the curb vehicle weight [kg]. Similarly, Figliozzi (2017) estimated the kg of CO2e caused by drone production as:

$$CO2e_{drone} = e_{drone} \cdot m_{bodydrone} \tag{2}$$

where e_{drone} is the emission coefficient for drone parts [kg CO2e/kg] and $m_{body\ drone}$ is the weight of drone without payload and battery [kg].

For the electric vehicles, $m_{body\ truck}$ was computed as the difference between the tare weight of the vehicle and the battery weight:

$$m_{bodytruck} = m_{tare} - z_{batt} \cdot cap_{batt} \tag{3}$$

where z_{batt} is the battery energy density [kg/KWh] and cap_{batt} is the nominal battery capacity [KWh].

A similar approach was used by Yang et al. (2018) and Figliozzi (2017) to estimate the impact of battery production, using the following formula:

$$CO2e_{battery} = e_{battery} \cdot cap_{battery} \cdot nbatteries \tag{4}$$

where $e_{battery}$ is the emission coefficient for battery production, $cap_{battery}$ refers to the nominal battery capacity, and *nbatteries* refers to the number of batteries per vehicle. In particular–as emerged from the interview–two batteries are often employed in drones to increase the flight range. Following Stolaroff et al. (2018), we computed the usable battery capacity considering the nominal capacity and the safe depth of discharge. Vehicles' weight and battery size were taken directly from the interview and from the truck manufacturers' websites, more specifically, from the WorkHorse C1000 and Mercedes-Benz Cargo 4500 technical specifications (Workhorse, 2020; Mercedes-Benz, 2020). All the production phase input values can be found in Appendix B and Appendix C.

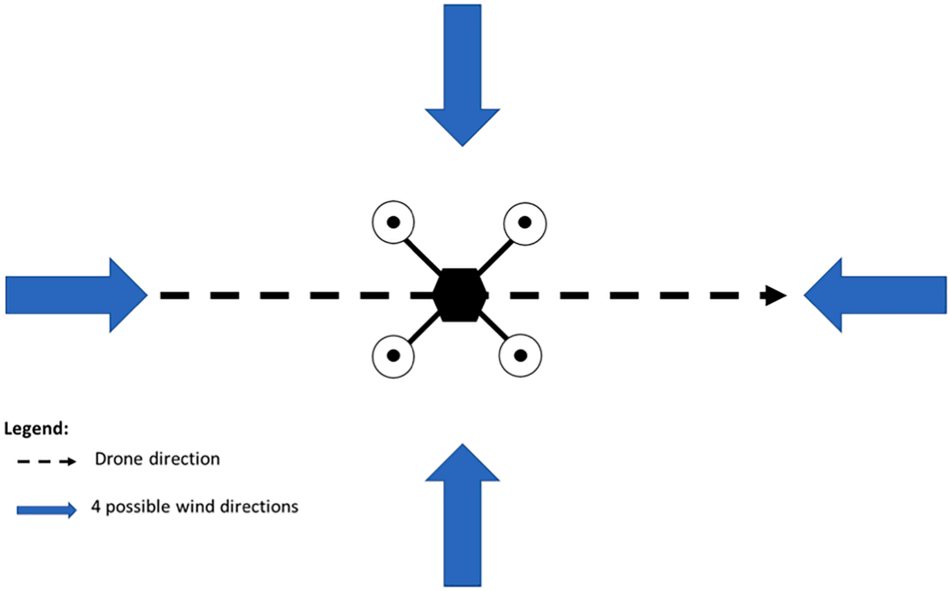

Fig. 3. Possible wind directions representation.

The end-of-life phase of vehicles and batteries may lead to significant CO2e savings when the appropriate recycling processes are put in place. Emissions savings from recycling are computed as a fraction of the production phase emission (Yang et al., 2018). For instance, as reported in Appendix B, the percentage of Li-ion battery production emissions savings due to recycling is estimated to be 19% (Sullivan and Gaines, 2012).

3.2.3. Use phase

To assess the emissions caused during the use phase, it was necessary to compute the vehicles' energy consumption. Section 3.2.3.1 and 3.2.3.2 respectively explain emissions of the drone and truck use phases.

3.2.3.1. Drone. Following Kirschstein (2020), we determined energy consumption by the sum of the energy demand for each step of the drone delivery journey (each notation is available in Appendix C).

$$E^{UAV}(d_d, v_d, m) = \frac{t_{tol} \cdot (P^{UAV}(m, v_d, \gamma_{tol}) + t_{tol} \cdot P^{UAV}(m, v_d, -\gamma_{tol})) + t_{lf} \cdot P^{UAV}(m, v_d, 0) + (t_{hover} + t_w) \cdot P^{UAV}(m, v_{wind}, 0)}{\varepsilon_{charging} \cdot \varepsilon_{transmission} \cdot \varepsilon_{engine}} + \frac{(2t_{tol} + t_{lf} + t_{hover} + t_w) \cdot P^{int}}{\varepsilon_{charging}} \tag{5}$$

The first addend of Eq. (5), adapted from Kirschstein (2020), represents the energy consumed during takeoff, landing, level flight, and hovering, while the second addend of the equation computes the energy consumed by the internal electronics devices. Both hovering before landing at the customer destination and waiting for the truck were considered. The average drone waiting time before being retrieved by the truck was computed as the difference between the average drone flight duration and the average time between two consecutive stops by the truck. P^{UAV} refers to the power demand of the drone and was computed for each of the four phases of a delivery flight: (i) takeoff, (ii) level flight, (iii) hovering, and (iv) landing (Kirschstein, 2020). The power demand, as in Langelaan et al. (2017), can be derived by summing the power needed to counteract the air drag (P^{air}) and the rotors' air drag ($P^{profile}$) as well as the power needed to lift the drone (P^{lift}), to climb (P^{climb}), and to keep the internal electronics devices functioning (P^{int}).

$$P^{UAV} = P^{air} + k \cdot P^{lift} + P^{profile} + P^{climb} + P^{int} \tag{6}$$

The detailed formulas to compute P^{UAV} are displayed in Appendix C. (For an extensive study on drone energy consumption, see Kirschstein, 2020, and Langelaan et al., 2017.).

All the input values–available in Appendix C.3–refer either to Kirschstein (2020) or to the the information gathered during the interview with the drones' producer. Specifically, the values of drone weight and flight speed estimated in Kirschstein (2020) were not confirmed by the drone manufacturer.

As emerged from the interview, the overall drone weight considered in this study is given by:

(i) the drone tare without the battery, 8 kg (while Kirschstein (2020) estimated it to be only 2 kg). It should be noted that drone specifications are taken from a producer specialized in drones for photography. Despite the payload similarities, the tare of the delivery drone could be slightly higher due to further adaptations.

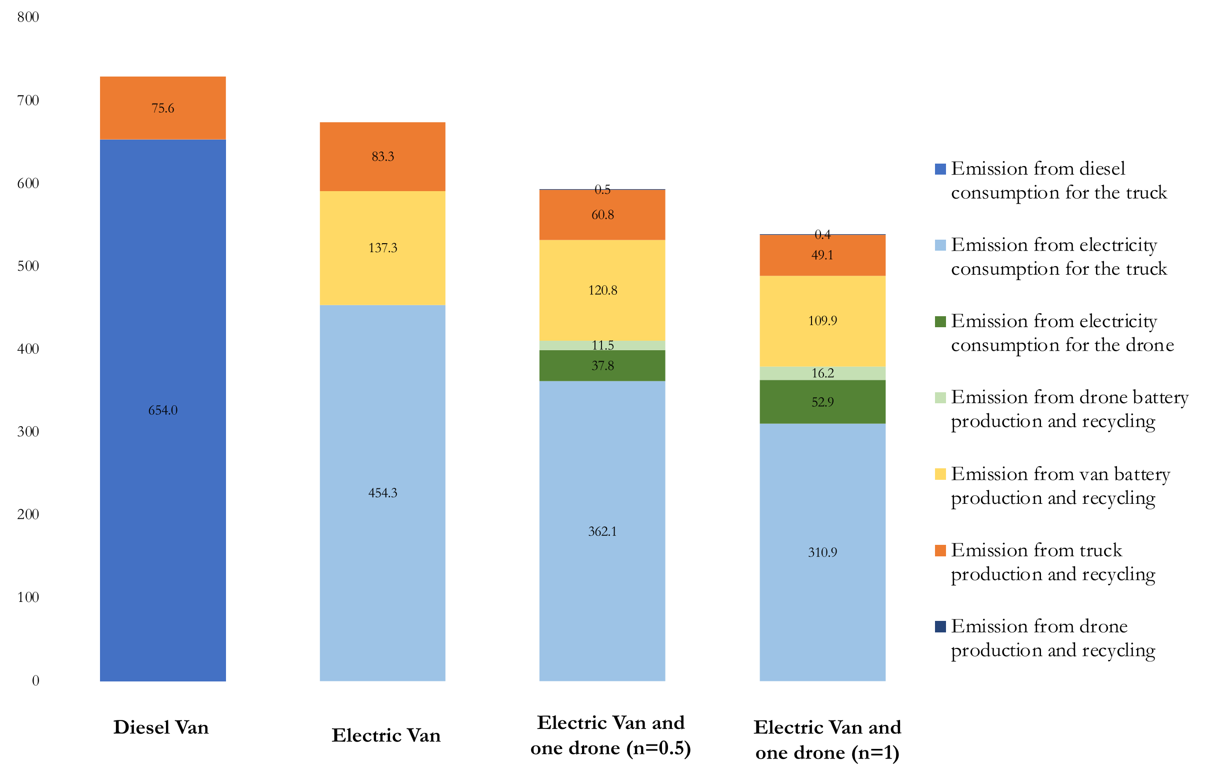

Fig. 4. Breakdown of LCA [gCO_2/delivery] (conservative scenario, low wind speed, low traffic condition, low delivery density, high carbon intensive scenario).

(ii) the total weight of the batteries, 6.15 kg, computed as 2 batteries of 0.8 kWh each, with a density of 0.26 kWh/kg (while Kirschstein (2020) estimated it to be 10 kg, for a battery capacity of 1.5 kWh).
(iii) the payload, 2.5 kg from the truck to the customer and 0 kg on the way back to the truck (in accordance with Kirschstein,2020).

Regarding the average speed, Kirschstein (2020) assumed a constant speed in all phases of a drone's flight, while in this research the drone speed during takeoff and landing is assumed to be lower than the speed during level flight, in accordance with the technical specifications of the octopeter under analysis. The value of the level flight speed has been set to 17 m/s (61 km/h), while the landing/takeoff speed is on average 2.3 m/s (8.3 km/h). Four possible wind directions were considered in the model, encompassing cross-, head-, and tailwind conditions. Crosswind and constant headwind conditions worsen drone energy requirements (Stolaroff et al., 2018; Kirschstein, 2020), impacting the drone speed and the power to counteract the drag force. Since during a real-life drone delivery journey, drone flight path and wind direction are continuously changing, each scenario can be considered equiprobable. The average drone energy consumption, as well as the average flight duration, was computed by averaging the results for each of the four wind directions shown in Fig. 3.

3.2.3.2. Vehicle. Following Kirschstein (2020), we started the ground vehicles' energy consumption model from the computation of the vehicle power demand, as for the drones.

$$P^M = P^{air} + P^{roll} + P^{grade} + P^{inert} \tag{7}$$

P^{air} stands for the power to counterbalance the air drag force, P^{roll} the rolling resistance, P^{grade} the gravity force in case of sloped road, and P^{inert} the inertial force.

The model estimated the fuel consumption for internal combustion engine vehicles (DV) and energy consumption of electric vehicles (EV). Kirschstein and Meisel (2015) approximated the engine transmission efficiency for a DV as: $\varepsilon_{DV} = 0.9 - 0.72^{-0.077 \cdot v^{1.41}}$. Moreover, they provided an expression to compute the fuel consumption given constant speed, fuel consumption rates, acceleration coefficients, and nominal engine power.

$$F^{DV}(d_t, v_t, n^{acc}) = \frac{d_t}{v_t} \cdot f^{idle} + \frac{f^{full} - f^{idle}}{\varepsilon_{DV}(v_t) \cdot P} P^M(v_t, d_t, n^{acc}) \tag{8}$$

Regarding EVs, the overall engine efficiency was given by the product of the charging efficiency, transmission efficiency, and engine efficiency: $\varepsilon_{charging} \cdot \varepsilon_{transmission} \cdot \varepsilon_{engine}$. Given the power demand and the overall efficiency, the resulting energy consumption for

EVs was given by:

$$E^{EV}(d_t, v_t, n^{acc}) = \frac{d}{v} \cdot \frac{P^M(v, d_t, n^{acc})}{\varepsilon_{charging} \cdot \varepsilon_{transmission} \cdot \varepsilon_{engine}} \tag{9}$$

Van weight affects the amount of power required during delivery operations. Since the number of delivered parcels changes significantly among the alternatives, in this study the average van weight was computed as $m_{tare} + \frac{Q_{td} \cdot m_{payload}}{2}$, where Q_{td} s stands for the sum of the deliveries done by truck and drone (if present) and $m_{payload}$ is the mass of the single delivery.

Losses in transmission and distribution, expressed as % of the electricity output lost due to inefficiency along the grid, should be taken into account. The value of this parameter was retrieved from the World Bank database (World Bank, 2018) and refers to the Italian electrical grid. It is worth noting that the losses along the electric grid do not differ significantly among European countries, where most of the countries have losses ranging between 5% and 8% of the output. Finally, fuel emissions were obtained by combining well-to-tank (WTT) emissions, caused by oil extraction, refining, and transport, and tank-to-well emission (TTW), related to the burning of oil to feed the combustion engine in the truck.

3.2.4. Allocation to the functional unit

In an LCA analysis, production emission values for trucks, drones, and batteries must be allocated to the chosen functional unit (ILCD, 2010), which is the single package delivered by either truck or drone.

Concerning ground vehicles' and drones' production phases, we allocated emissions to single deliveries by dividing the overall production emission value by the total number of deliveries during the vehicle's life cycle in each specific scenario.

Regarding batteries' production emissions, the allocation followed a three-step procedure. First, we computed the emission per kWh used by dividing the overall production emission by the maximum number of cycles before a battery's end of life. The battery life cycle is affected by the degradation of the battery itself, measured by the State of Health (SOH), an indicator of the battery storage capabilities compared to the original conditions. According to Pelletier et al. (2017), a battery's operating conditions, charging operations, and environmental conditions affect the maximum number of cycles. The emissions caused by cycles were then divided by the battery usable capacity to obtain the emissions caused by each kWh used by the vehicle, as shown in the formula below:

$$Emissions\ per\ kWh\ used = \frac{GHG_{battery}}{n_{cycles} \cdot cap_{battery}} \tag{10}$$

where n_{cycles} is the maximum number of cycles.

Second, the emissions per working shift were computed by multiplying the value obtained in the previous step by the sum of daily energy consumption of the drone and the EV.

Third, the emissions per package can be found by dividing daily emissions by the number of packages delivered in a day. The LCA time span is 10 years, which is the average useful life span of a delivery van (Figliozzi, 2017). Drones' and batteries' residual useful lives at the end of the LCA time span were taken into consideration for the production phase emissions computation.

Finally, use phase emissions were allocated to single parcels by dividing the daily energy consumption of the delivery system by the combined number of parcels delivered by the truck and drone.

3.3. Total cost of ownership

Following the TCO approach employed by Yang et al. (2018), we categorized the relevant cost items throughout the assets' useful lives into (i) purchasing costs, also referred to as capital expenditure (CAPEX); (ii) operational expenses (OPEX); and (iii) end-of-life residual value. The cost of capital, which affects the discounted cash flows, was assumed to be 7%, obtained by averaging the weighted average cost of capital (WACC) of Amazon, Alphabet, and UPS (gurufocus.com, 2020).

In accordance with Doole et al. (2020), for any cost items expected to change in the future, we provided conservative, optimistic, and future values. These three scenarios were used to assess the results' robustness in the sensitivity analysis. The TCO value refers to the overall cost attributable to a delivery van, with or without a drone, throughout its life cycle. As for the LCA, to increase comparability between alternatives characterized by a different capacity in terms of daily deliveries, we allocated the overall TCO to the single delivered parcel.

3.3.1. Purchasing cost

The specific DV chosen for the analysis was the Mercedes-Benz Sprinter, whose price can be found on the manufacturer's website. Since the price of Workhorse C1000, the EV chosen for the analysis, is not publicly available online, we estimated its cost by looking at comparable trucks, and it was assumed to decrease in the optimistic and future scenarios, reaching a cost value similar to the DV. Consistently with the LCA, the TCO analysis adopted a model of octocopter adapted to perform e-commerce last-mile delivery. As emerged from the interview, the drone cost is estimated to be about € 20,000. A reduction of the average drone price of 50% in the optimistic scenario and 75% for the future scenario was assumed (Doole et al., 2020). Van battery cost was estimated by taking into consideration the Workhorse C1000 battery capacity and the battery cost per kWh, retrieved from Doole et al. (2020). Values are collected in Appendix E.

Table 2
Operative expenses cost categories.

Parameter	Yang et al. (2018)	Doole et al. (2020)	Considered in this analysis
(i) Fuel and Electricity Cost	x	x	x
(ii) Drone Battery Cost	x	x	x
(iii) Maintenance Cost	x	x	x
(iv) Insurance Cost		x	x
(v) Labor Cost	x	x	x
(vi) Airspace Cost		x	x

3.3.2. Operational expenses

Operational expenses are the costs occurring during the delivery system business operations. The cost categories considered in the analysis were taken from Yang et al. (2018) and Doole et al. (2020), as shown in Table 2.

(i) Fuel cost and electricity cost refer to Italy (MISE, 2020)). The overall yearly fuel cost was obtained by multiplying the fuel cost by the daily average km traveled and by the number of workdays in a year. The cost of electricity was computed in the same way, considering the kWh consumed instead of the km traveled.

(ii) Contrary to the van battery cost, the cost for the drone battery was classified as OPEX since batteries are to be changed more often, even more than once per year. Drone battery cost was obtained by the following formula:

$$Yearly\ battery\ cost = battery\ cost\ per\ kWh\ used \cdot daily\ energy\ consumption \cdot number\ of\ workdays\ per\ year \tag{11}$$

(iii) DVs' maintenance cost rate [€/km] was taken from Yang et al. (2018), who referred to a study authored by van Vliet et al. (2010). Following Yang et al. (2018), we assumed the EV maintenance cost to be half that of DVs due to the lack of transmission and engine maintenance and a generally lower number of components (Siragusa et al., 2022). Yearly maintenance cost can be computed by multiplying the maintenance cost rate by the yearly kilometers traveled by truck.

(iv) Drones' and vans' yearly maintenance and insurance cost values were obtained from the interview and IVASS (2020), respectively.

(v) The labor cost was computed starting from the average hourly salary for logistics operators in Italy (Repubblica, 2016). Drone pilots, together with delivery truck drivers, were assumed to belong to the category of logistics operators.

(vi) Finally, the TCO analysis included a possible future airspace cost for drones, which can be seen as a form of taxation aimed at controlling sky congestion. Conservative, optimistic, and future scenarios were considered to estimate the value of the hourly airspace cost, as in Doole et al. (2020). The airspace cost was computed as follows:

$$Yearly\ airspace\ cost = hourly\ airspace\ cost \cdot number\ of\ working\ hours\ per\ day \cdot number\ of\ workdays\ per\ year \tag{12}$$

OPEX cost values are given in Appendix F.

3.3.3. Residual value

Yang et al. (2018) argued that the end of life of vehicles' bodies and batteries should be considered a source of revenue since materials can be recycled and some pieces resold as spare parts. This research, following Yang et al. (2018), assumed a recovery rate of 5% of the initial cost for trucks' bodies and batteries. The same recovery rate was assumed for drones. Asset residual value, similarly to the LCA end-of-life analysis, was considered for vehicles and batteries.

4. Results and discussion

During the interpretation phase, an extensive sensitivity analysis was performed. First, three scenarios were identified—namely, conservative, optimistic, and future. These scenarios combined the variables expected to change in the future: (i) the maximum number of battery charging cycles before battery end of life, (ii) the drone level of automation and consequently labor intensiveness, and (iii) the majority cost items, as in Doole et al. (2020). The battery life cycle directly impacted the LCA and TCO results since a shorter battery useful life increased the impact of battery cost and production emissions allocated to each delivery. According to Pelletier et al. (2017), for electric trucks with Li-ion cells batteries 1000 cycles per battery can be assumed for a conservative scenario, 2000 for an optimistic scenario, and 4000 for a future scenario. According to the interview, drones' Li-ion battery lifecycles ranges from 500 cycles in the conservative scenario, to 800 and 1000 cycle for the optimistic and future scenario, respectively. Concerning labor cost, a human pilot must monitor and guide the drone during all delivery operations in the conservative scenario. Conversely, in the optimistic scenario, AI manages the drone during takeoff and line-haul, but a pilot is needed during hovering and landing. Finally, in the future scenario, the drone is fully automated, and a human pilot is not needed.

Concerning the delivery density, the sensitivity analysis encompassed two scenarios: one in a rather rural area with a density equal to 1 delivery/km^2, and the second in a more suburban context with a delivery density of 20 deliveries/km^2. A delivery density higher than 20 deliveries/km^2 could reduce the distance between two consecutive delivery stops to less than 200 m. At such a level of delivery density, the assumption of a single delivery per customer location may not hold since there can be multi-store buildings requiring more

Table 3
Outcome of the routing, low wind speed and low traffic conditions.

Variable	Comments	Unit	Values					
			1 customer/km^2			20 customers/km^2		
Tot. cust.	Number of customers in the delivery area	-	3000			60,000		
Drones per truck	Number of drones per truck	-	0	1	1	0	1	1
n	Ratio between drone and truck deliveries	–	0	0.5	1.0	0	0.5	1.0
w	Swipe width	km	1.7	2.0	2.2	0.4	0.4	0.5
Daily T avail.	If energy demand exceeds battery capacity, one hour charging is required	h	7.5	7.5	7.5	7.5	7.5	7.5
Q_{td}	Combined number of customers served by truck and drone	–	78.2	107.0	132.6	115.9	168.4	218.8
Q_t	Number of customers served by truck	–	78.2	71.3	66.3	115.9	112.3	109.4
Q_d	Number of customers served by drone	–	0	35.7	66.3	0	56.1	109.4
d_t	Average distance between two consecutive destinations traveled by the truck	km	1.15	0.95	0.82	0.26	0.21	0.18
d_d	Average drone flight distance between two consecutive truck stops	km	0	1.11	0.85	0	0.25	0.20
t_t	Average truck traveling time between two consecutive destination	s	129.9	106.4	92.6	29.0	23.8	20.7
t_d	Average drone flight traveling time between two consecutive truck stops	s	0	112.8	98.0	0	62.3	59.0
t_w	Drone waiting time (difference between the truck time between two consecutive stops and the drone one)	s	0	0	0	0	0	0
Tot dist.	Total truck route distance, including line-haul	km	139.7	150.6	158.6	79.4	85.1	89.7

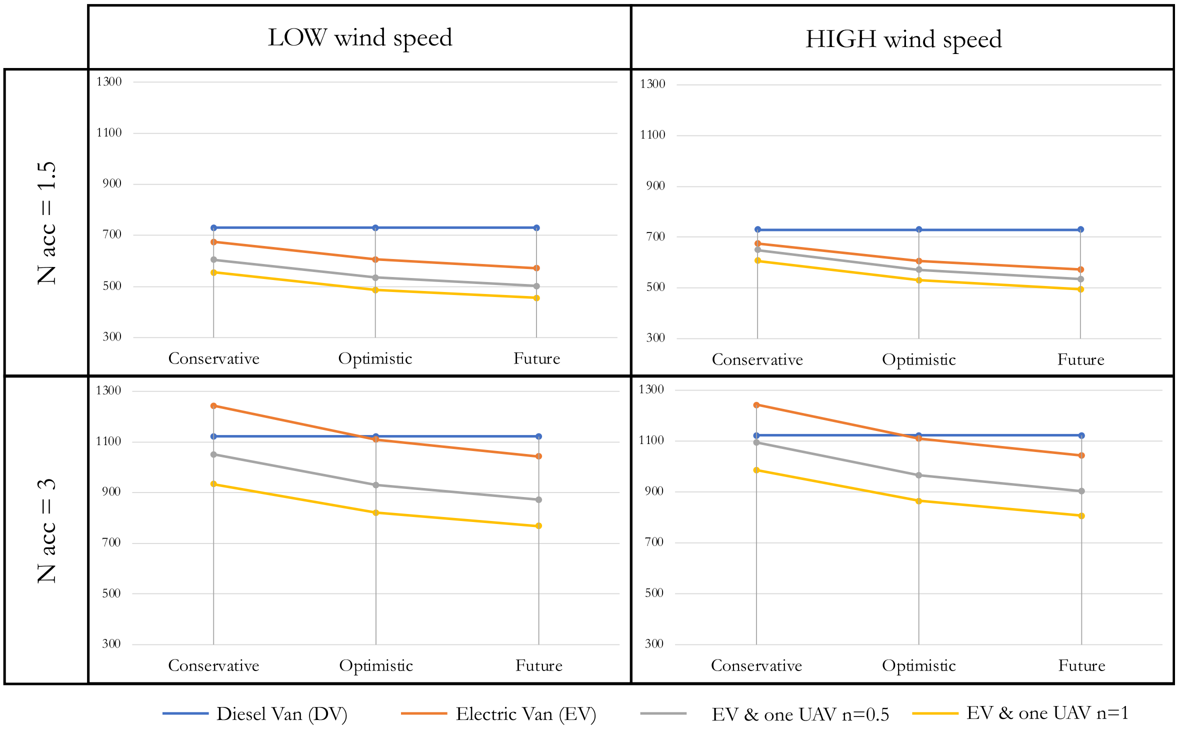

Fig. 5. gCO_2/delivery with customer density of 1 customer/km^2 (high carbon intensity scenario).

than one delivery.

Two values for the drone utilization rate, expressed as the ratio between deliveries done by drone and ones done by truck, have been considered, following Campbell et al. (2018). They noted that 1 is the maximum value of the utilization rate since a drone cannot perform more deliveries than a truck due to the logistics system configuration. Indeed, the model assumes that a drone must be launched and retrieved at two consecutive delivery stops, while the truck is stationary. Moreover, Campbell et al. (2018) considered an intermediate value of 0.5, which means that a drone performs half of the deliveries done by a truck.

An additional variable for the sensitivity analysis is the truck acceleration frequency coefficient, which impacts the amount of energy consumed by the electric truck. According to Kirschstein (2020), this coefficient is affected by the type of road and traffic conditions. In medium traffic conditions, n_{acc} is estimated to be 0.1, 1, and 4 in motorways, primary roads, and urban roads, respectively. In this study, LCA results were computed for two frequency acceleration coefficients: 1.5 and 3.

Another variable subjected to the sensitivity analysis was wind speed. Different values of wind speed were used in the sensitivity

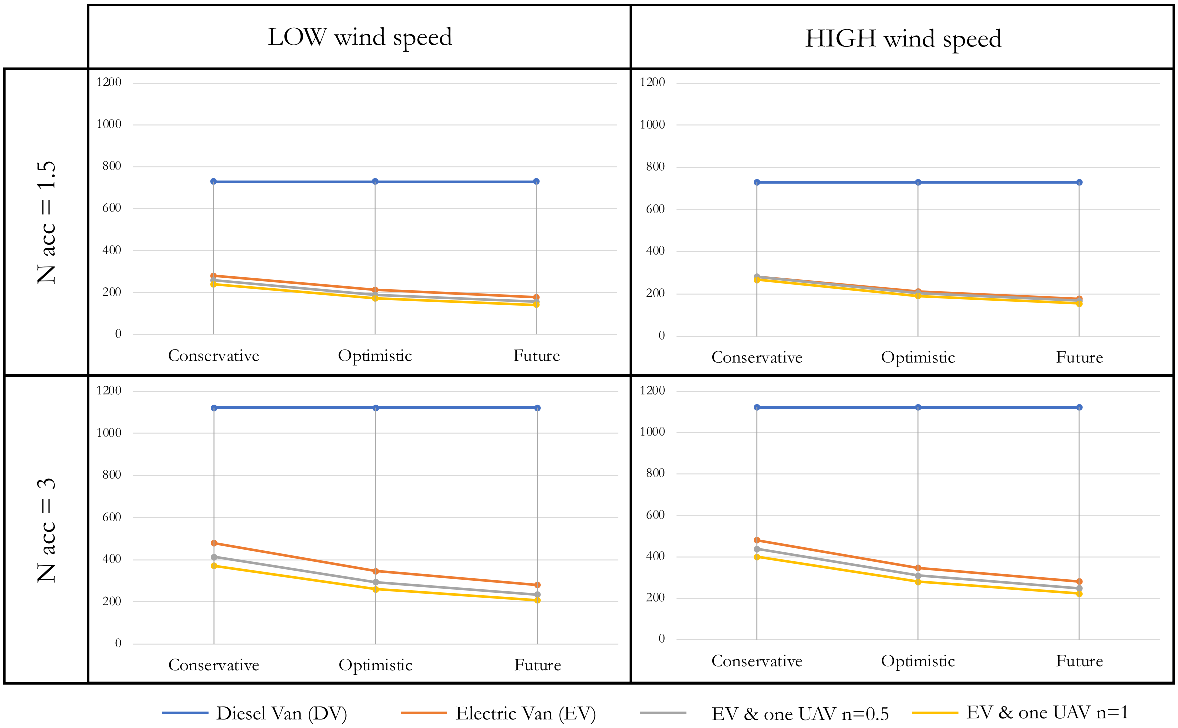

Fig. 6. gCO_2/delivery with customer density of 1 customers/km^2 (low carbon intensity scenario).

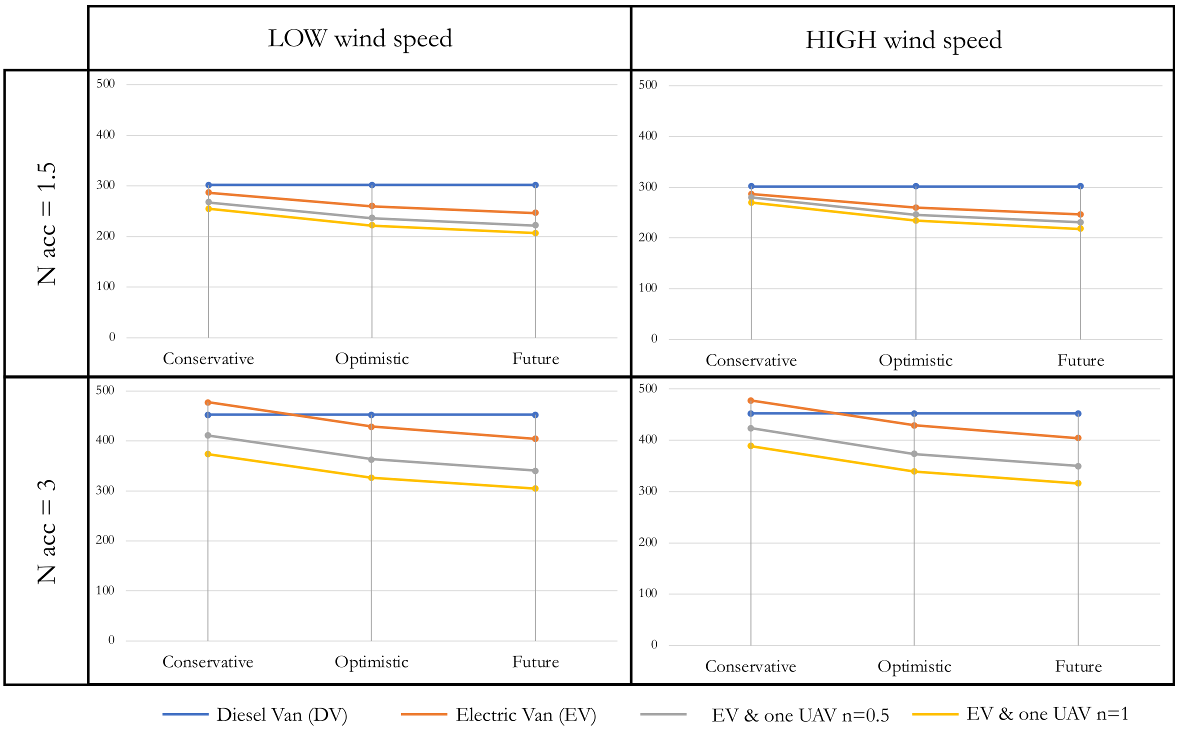

Fig. 7. gCO_2/delivery with customer density of 20 customer/km^2 (high carbon intensity scenario).

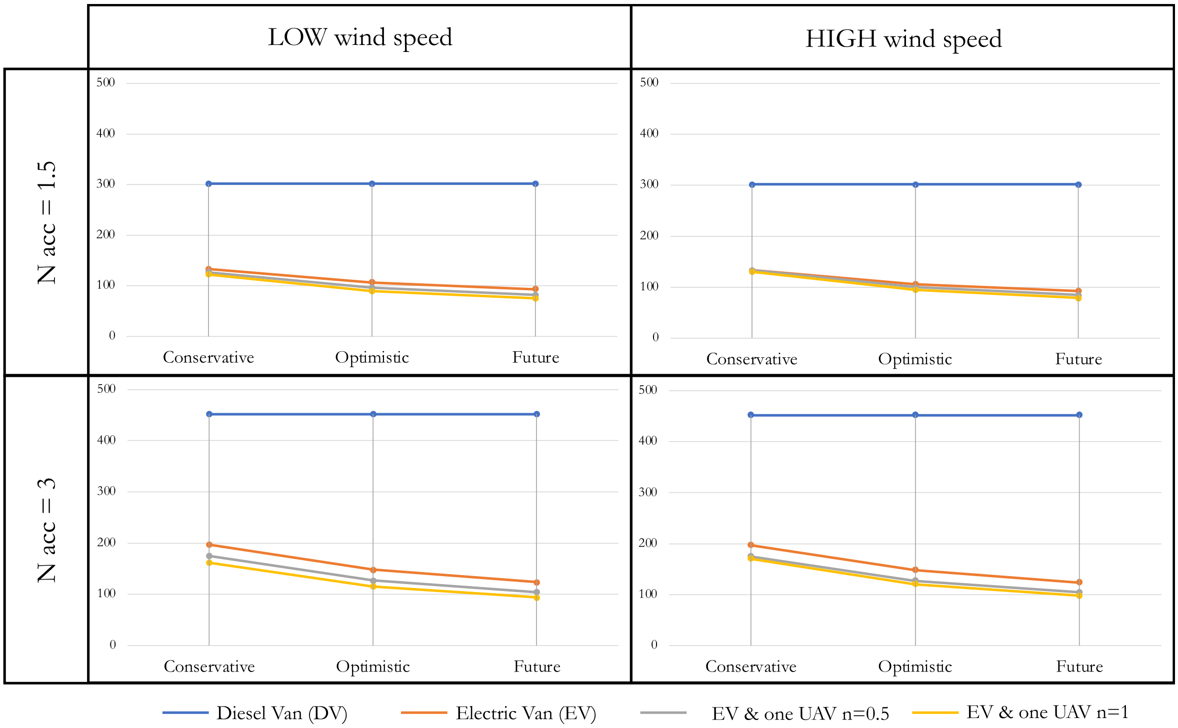

Fig. 8. gCO_2/delivery with customer density of 20 customer/km^2 (low carbon intensity scenario).

analysis—namely, 0 m/s (low wind speed scenario) and 12 m/s (high wind speed scenario) (Kirschstein, 2020).

Finally, the amount of use phase emissions is affected by the electricity production mix since each production mix leads to a different amount of CO2e per kWh of electricity produced (see Appendix D). Two different electricity production mixes were considered: the French one and the German one. These electricity mixes were chosen because they differ significantly in terms of environmental impact. The French grid relies mainly on nuclear energy, which is less polluting than carbon (EEA, 2018). The German electricity mix is more carbon-intensive, thus leading to high emissions per kWh produced (EEA, 2018).

Relying on the model and input values, Table 3 shows the results of the vehicle routing, which will be the basis for the LCA and TCO. The data refers to the daily route of a truck (with and without a drone) in the conservative scenario assuming low wind speed and low traffic condition.

4.1. Life cycle assessment results

Figs. 5, 6, 7, and 8 show the results, including the performance in terms of emissions per delivery of the different logistics alternatives, in the three scenarios with varying acceleration frequency coefficient, delivery density, and wind condition. In Figs. 5 and 7, the German electricity production mix is assumed, while the French one is adopted for Figs. 6 and 8.

The outcome of the study shows that the truck-drone delivery system leads to significant savings in terms of CO2e per delivery regardless of delivery density, acceleration frequency coefficient, battery useful life duration, wind condition, and energy production mix. Nevertheless, the additional battery emissions for drones partially offset the gains obtained by the truck-drone system, especially in the conservative scenario, where batteries have the shortest useful life. Indeed, moving from a conservative scenario to a future scenario, EVs, with and without drones, become even more environmentally friendly. As expected, EVs perform better if low-carbon-intensive electrics grids are used. Furthermore, the LCA analysis demonstrates that exploiting a drone up to the maximum utilization rate (n = 1) is environmentally more convenient than using the drone for a fraction of the potential drone deliveries. Fig. 4 provides the system's emissions breakdown, highlighting the relevance of truck use-phase emissions, which account for more than 60% of the overall emissions. Compared to traditional delivery, a truck equipped with drone has (i) lower use phase emissions, due to the route optimization enabled by the truck-drone delivery system, and (ii) lower production phase emission since more parcels can be delivered throughout a truck life cycle. Drone-related emissions are instead marginal, even for the alternative with the maximum drone utilization rate, due to the limited distance traveled by the drone.

Overall, the production and recycling phase has a significant impact on the truck-drone life cycle emissions, often being the differentiating factor driving emissions reductions compared to ground vehicle delivery, as shown in Appendix H. Ground vehicles' and drones' energy consumption per unit of distance are primarily affected by traffic conditions and wind speed, respectively (see Appendix G.1 for more details). Appendix G.2 provides the use phase energy requirement per delivery for each logistics alternative, identifying delivery density and traffic condition as the two most impactful variables. Other variables, including wind speed, do not

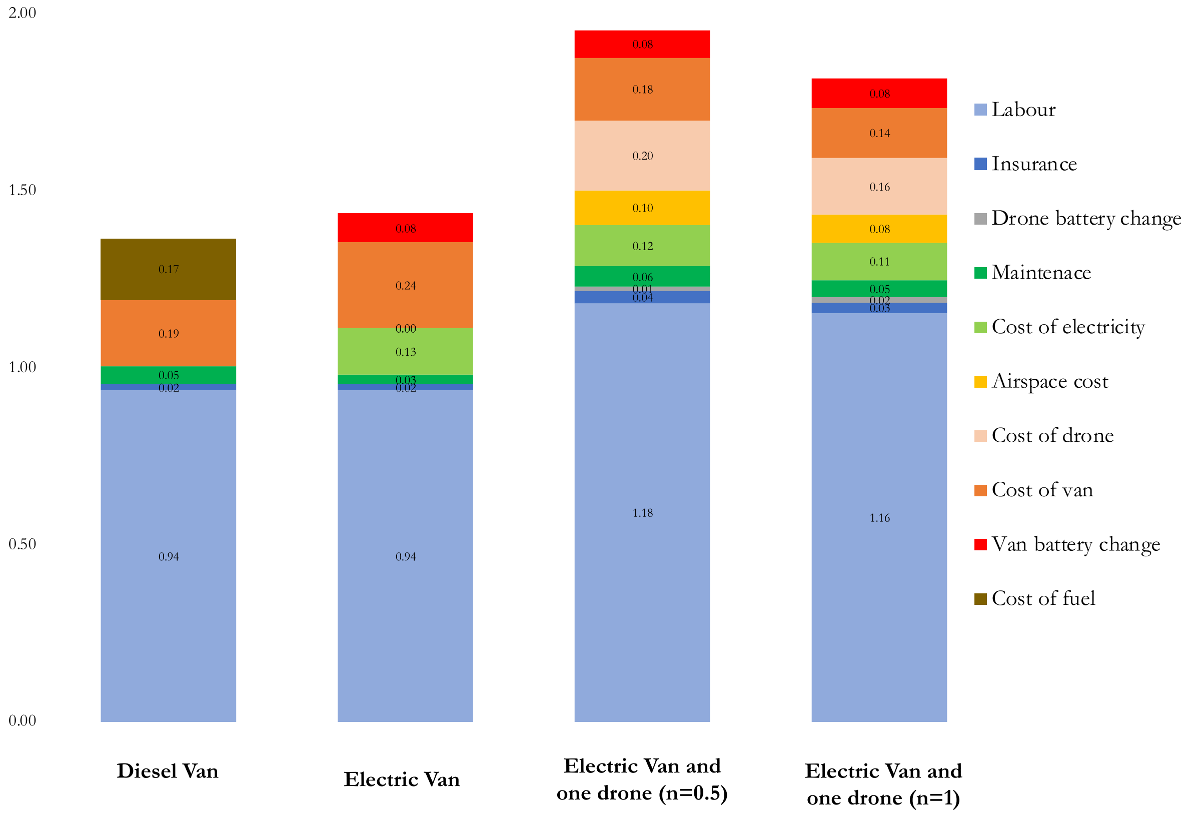

Fig. 9. Breakdown of TCO [€/delivery] (conservative scenario, low wind speed, low traffic condition, low delivery density).

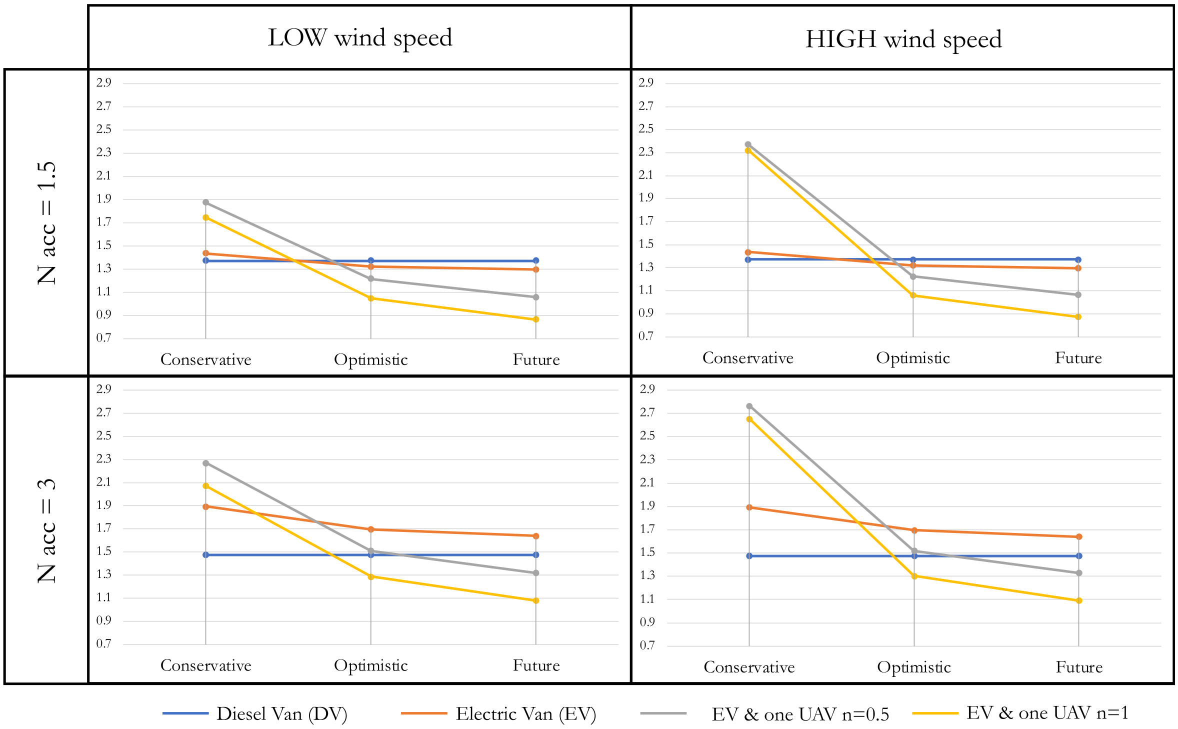

Fig. 10. €/delivery with customer density of 1 customer/km^{2}.

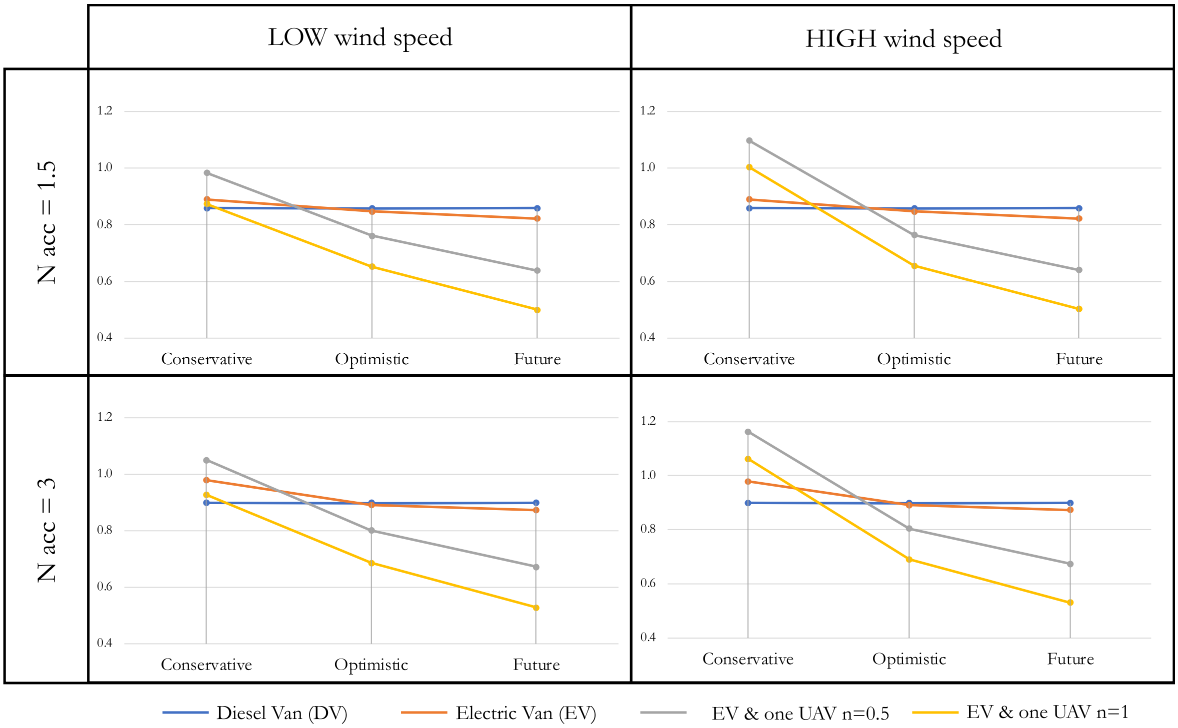

Fig. 11. €/delivery with customer density of 20 customers/km^{2}.

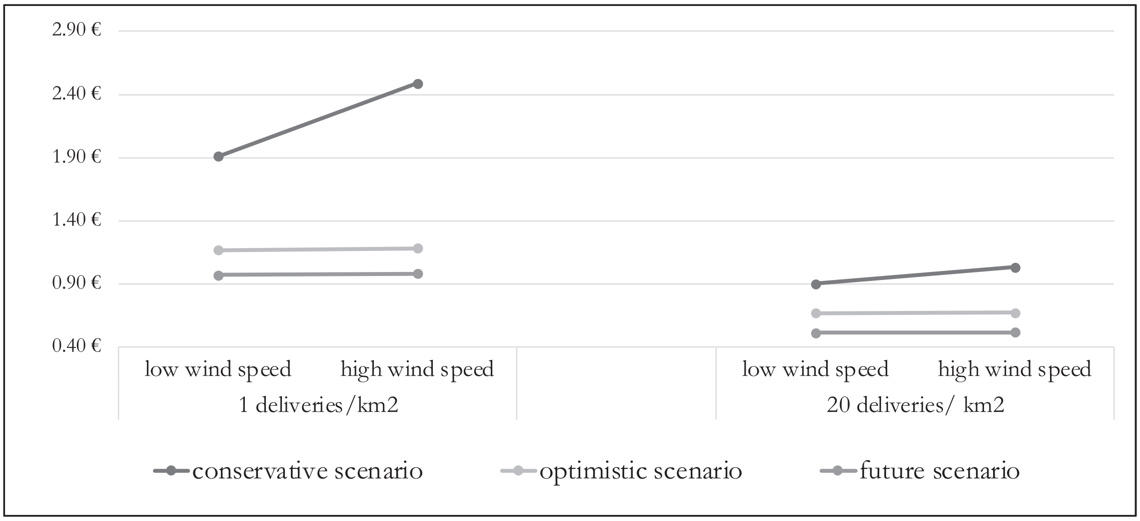

Fig. 12. Comparison between the 4 situations of the TCO sensitivity analysis [€/delivery].

have a significant impact on the energy consumption per delivery.

The bottom right corner of Fig. 5 shows the results assuming the German electricity production mix, high acceleration frequency coefficient, the most rural delivery area, and the highest wind speed. This can be considered the worst-case scenario for drones, since the German production energy mix is carbon-intensive and one of Europe's most polluting in terms of kg of CO2e per kWh produced (EEA, 2018). Moreover, a rural delivery area, which makes the delivery route longer, together with a high acceleration frequency coefficient force the electric van to stop for up to 1 h to recharge the battery. Indeed, the overall energy consumption for the truck exceeds the battery capacity only in this condition, and the battery charging time limits the number of parcels that can be delivered, worsening the LCA emission performance. Even in this scenario, the truck-drone joint system leads to a reduction of LCA CO_2e of more than 10% compared to DVs.

Table 4
Environmental comparison between fixed-depots studies and the present study.

	Delivery Scenario	Drone details [Typology of drone (payload transported in the first leg of the journey)] *	Energy requirement [Wh/delivery]
Figliozzi (2017)	NA (average customer distance from the depot is 13 km)$_1$	Quadcopter (5 kg payload)	562
Stolaroff et al. (2018)	Urban area (San Francisco)$_2$	Large octocopter (8 kg payload) Small octocopter (0.5 kg payload)	805 80
Kirschstein (2020)	Urban area (Berlin)$_3$	Octocopter (2.5 kg payload)	About 1500
Present study	Densely populated scenario: system boundaries from regional warehouse to customer$_4$	Octocopter (2.5 kg payload)	429

1. The delivery configuration consisted of a drone delivery from a warehouse. Value computed by the authors considering a two legs drone delivery journey with average customer distance from the depot equal to 13 km.
2. Results are computed in cases of a drone performing only one hop from urban warehouse to final customer (delivery range of 4.3 km). In the original paper, several drone alternatives were considered. For the purposes of the comparison, only the large octocopter (up to 8 kg payload) is provided in the table.
3. The delivery configuration consisted of a drone delivery from an urban warehouse (delivery range of 9 km). In the original paper, several customer distributions and wind speed values were assumed. For the purposes of the comparison, only the scenario with uniformly distributed customers is provided and the result is the average of all wind conditions.
4. The delivery journey simulated in this study starts from the regional warehouse and ends at the final customer (total distance covered by truck is 89 km in the most densely populated scenario, and average distance traveled by drone is 0.2 km). For the purposes of the comparison, in this table only the most densely populated scenario is provided. The value is the average of the various traffic and wind conditions.
* The delivery system assumption in all papers listed in Table 4 is that the drone carries an empty payload in second leg of its journey.

4.2. Total cost of ownership results

As in the LCA, the TCO results were assessed against the same sensitivity parameters as shown in Figs. 10 and 11. The result interpretation highlights that the choice of the three scenarios—conservative, optimistic, and future— and wind speed are the variables with the strongest impact on the variation among the different alternatives. The truck-drone joint delivery system is not economically beneficial in the conservative scenario leading to an increase in the last-mile delivery cost. Conversely, moving to the optimistic and future scenario, drones can lead to significant cost savings. Labor is the most relevant cost element, accounting for more than 65% of the overall cost. Economic savings from truck-drone delivery come mainly from the reduction of this cost item, due to the increased delivery capacity during the standard driver working shift, resulting in a more optimal truck-filling rate. An exemplary cost breakdown is provided in Fig. 9, showing the detailed cost items computed for one of the combinations of the various settings in the sensitivity analysis.

Fig. 12 summarizes the economic performance of a truck-drone joint delivery system with varying wind conditions. It was obtained by averaging TCO values for high and low customer density and acceleration frequency coefficients. The three scenarios adopted for the sensitivity analysis were studied separately. The conservative scenario has the highest variability. On the contrary, the optimistic and future scenarios are not influenced by wind conditions, and their performance is stable. This demonstrates that in the future, once AI and regulations allow drones to be automated, wind conditions will not matter significantly as far as cost is concerned.

5. Conclusion

5.1. Contribution

This study bridges the gap in the literature for a comprehensive environmental and economic analysis of an intermodal truck-drone last-mile delivery system. The analysis used both primary and secondary data and the outcome of the simulated logistics system, leveraging a routing optimization model (Campbell et al., 2018), a vehicle energy consumption model (Stolaroff et al., 2018; Kirschstein, 2020) and a last-mile logistics economic analysis (Yang et al., 2018; Doole et al., 2020). This study demonstrates that a truck-drone multimodal delivery system is environmentally convenient, and this result was gained under any scenario studied in the sensitivity analysis: the delivery system with drones always leads to the lowest emission per parcel delivered, even with a high-carbon-intensive electrical production mix and assuming conservative estimation for a battery's useful life. Under the assumptions considered by this study, delivering a parcel with the truck-drone system emits, on average, 351 gCO2e (versus about 652 and 414 gCO2e/delivery with a diesel truck and electric truck, respectively). Considering the growing importance of reducing the transport industry's environmental footprint, the quantification of the LCA emissions provided by this research could be useful for logistic operators' decision-making on potential investments in a truck-drone delivery system.

The TCO analysis results show that if a human pilot is needed, adding a drone to a delivery truck is not economically beneficial, causing losses compared to the delivery with a diesel van, which is around 37% more convenient. Moving to the optimistic scenario, implementing a delivery system with drones leads to a cost reduction ranging between 12% and 26% compared to traditional delivery cost. These gains become even more significant in the future scenario, where AI is capable of fully controlling drone operations. In this scenario, on average 36% of the total costs can be saved with a truck-drone joint delivery system. From a practitioner's point of view, considering the last-mile delivery low margins, these savings are particularly noteworthy.

5.2. Comparison with fixed-depots system

Even if the results of the present study about truck and drone delivery are not easily comparable with previous studies due to different assumptions and scenarios, some considerations may arise. In particular, the truck-drone delivery system seems to cause lower emissions per parcel not only when compared to traditional systems with trucks but also when compared to drone delivery systems with fixed depots. Contrary to the present study, those investigating solutions with fixed depots concluded that, on average, deliveries with drones can cause more emissions compared to ground-based solutions. Table 4 compares the use phase energy requirement of three fixed-depot delivery systems (Figliozzi, 2017; Stolaroff et al., 2018; Kirschstein, 2020) with the one in the present study (for a more detailed discussion on drone energy consumption models from previous studies, see Zhang et al., 2021). Previous studies differ in terms of system boundaries and payload, not allowing a direct comparison of life cycle values. Moreover, even the boundaries of the use phase itself vary between studies. The present study analyzed a truck delivery journey from a distribution center to final customers (with an average daily traveled distance in urban areas equal to 89 km). In contrast, existing fixed-depot studies have focused only on the drone journey from an urban depot to final customers (less than 15 km delivery distance).

Comparing the present study with studies assuming a similar payload (2.5 kg on the first the leg of the journey and empty paylod on the second leg), it emerges that in Kirschstein (2020) the use phase energy requirement is about 1500 Wh/delivery. This study shows that the truck-drone delivery system leads to an average energy requirement of 429 Wh/delivery, even by including a wider scope of analysis (i.e., delivery from a distribution center instead of an urban depot). The truck represents a mobile depot for the drone along the delivery path, with the drone being employed only in the very last mile, increasing the total number of deliveries during a shift. A truck-drone delivery system does not require additional infrastructures, resulting in higher flexibility compared to a fixed-depots system. There are indeed no constraints due to the availability of a physical network of depots.

5.3. Further research

Due to the inherent complexity of modeling a delivery system and the novelty of the technology involved, several assumptions were made. These assumptions made the analysis feasible but may limit the results' accuracy.

Single delivery per destination: Only one delivery per destination is assumed, which is a relevant assumption that particularly affects the ground-based delivery performance since a truck can deliver more than one parcel per destination, as may happen for multi-story apartment buildings. This assumption limits the results' application to rural or suburban areas, where it is reasonable to assume one delivery per destination.

Delivery truck logistics parameters: Truck speed is assumed to be constant, and a simplified truck trajectory has been used, following Campbell et al. (2018). It would be interesting to perform a similar analysis simulating a real-world road network and changing vehicles' speeds accordingly.

Delivery drone logistics parameters: The assumption of a straight drone trajectory from the truck to the destination may not hold in real life. Drones may be required to take the route that minimizes risks for all the stakeholders involved. Thus, drone trajectory may not be straight, and it can change continuously due the dynamic nature of ground risk parameters.

Source of data: Real-world experiments would help test the accuracy of the model, such as the experimental tests on small quadcopters performed by Stolaroff et al. (2018) to validate their assumptions.

Drones always capable of performing delivery operations: It was assumed that drones can operate 300 days per year, like the ground-based alternatives. However, due to the novelty of the technology, it is difficult to estimate drones' capability to perform delivery operations in harsh weather conditions. Yowtak et al. (2020) included in their LCA analysis the possibility that, due to adverse weather, drones cannot always be used, and traditional delivery vans need to compensate for the temporary downtime of drones. To account for this possibility, the authors adopted as unit of analysis the biyearly emissions of the whole delivery system. Similar consideration may be adopted by future researchers.

Impact category selection: One specific impact category (i.e., gCO2e) has been used. However, it would be interesting to benchmark the performance of the logistics system under analysis according to different impact categories.

Comparison between a truck-drone and a fixed depots drone delivery system: To further improve the comparison between various drone delivery systems, each logistics alternative should be assessed under the same assumptions, system boundaries, and delivery scenarios. Future research efforts should focus on both environmental and economic assessment, allowing for a comprehensive discussion on the tradeoffs between systems.

Underlying logistics system: The present study considered a particular "mobile" depot system, which is a van equipped with a drone. This study assumed that trucks and drones can perform deliveries simultaneously. However, a variety of drone delivery configurations, present in the literature, are still to be assessed from both environmental and economic perspectives. These configurations range from variations of the truck-drone model assumed by this study (e.g., a truck waiting for its multiple drones to deliver parcels while the truck stops) to more diverse systems (e.g., a system where drones connect to the roof of autonomous cars to save energy and increase the delivery capacity (Yoo and Chankov, 2018) or where trucks perform delivery operations being resupplied by drones throughout the delivery journey (Dayarian et al., 2020)).

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.

Acknowledgements

We would like to express our gratitude to Italdron for its contribution by providing us with data about drones. The information was extremely important to conduct our study.

Appendix A. Underlying logistics system description

See Tables A1 and A2.

Table A1
Computations from Campbell et al. (2018) model.

Description	Formula
Swath width for the truck-only delivery system	$w = \sqrt{\frac{3}{\delta}}$
Average distance between two destinations for the truck-only delivery system	$d_t = \frac{w}{3} + \frac{1}{w \cdot \delta}$
Swath width for the truck-drone joint delivery with one drone per truck ($0 < n <= 1$)	$w = \frac{\sqrt{n+1} c_t + 2c_d}{c_t + 2c_d} \cdot \sqrt{\frac{3}{\delta}}$
Average distance between two destinations travelled by the drone in a truck-drone joint delivery system	$d_d = 2\frac{n}{n+1}\sqrt{(\frac{w}{3})^2 + (\frac{1}{\delta w})^2}$
Average distance between two destinations travelled by the truck in a truck-drone joint delivery system	$d_t = \frac{w}{3} \cdot \left(1 - \frac{n}{n+1}\right) + \frac{1}{w \cdot \delta}$
Overall delivery route time as function of v_t, v_{lt}, w, Q_{td}, where Q_{td} is the overall combined daily deliveries performed by truck and drone	$T = Q_{td} \cdot \left[\frac{\frac{1}{w\delta} + \frac{w}{3(n+1)}}{v_t} + \frac{s_t}{n+1}\right] + \frac{0.9027\sqrt{Delivery\ Area}}{v_{lt}}$
Truck variable cost [€/km]	$ct = \frac{Gross\ hourly\ salary}{v_t} + F^{DV}(d_t, v_t, n^{acc}) \cdot Fuel\ cost\ per\ liter$
Drone variable cost [€/km]	$cd = \frac{Gross\ hourly\ salary}{v_{lf}}$

Table A2
Inputs for the Campbell et al. (2018) model.

Parameter	Description	Unit of measure	Value	Source
Delivery Area	Delivery Area	m^2	3200	Campbell et al. (2018)
v_t	Truck Delivery Speed	m/s	8.9	Campbell et al. (2018)
v_{lt}	Truck Linehaul Speed	m/s	17.8	Campbell et al. (2018)
T	Shift Duration	h	7.5	Campbell et al. (2018)
s_t	Average fixed time for a delivery stop by truck	h	0.05	Assumption
δ	Delivery Density	Deliveries/km^2	–	Discussed in the sensitivity analysis
n	Ratio Between Drone Deliveries and Truck Deliveries		–	Discussed in the sensitivity analysis

Appendix B. Production and Recycling Phase

See Tables B1 and B2.

Table B1
Input values for vehicles and batteries production emission.

Parameter	Description	Unit of Measure	Value	Source
e_{truck}	Emission coefficient for truck	kg CO2e/kg	8	Lee et al. (2013)
e_{drone}	Emission coefficient for drone	kg CO2e/kg	9.3	Figliozzi (2017)
$e_{battery}$	Emission coefficient for battery	kg CO2e/kWh	141	Figliozzi (2017)
$m_{tare\ DV}$	DV tare weight	kg	2,670	Mercedes-Benz Vans (2020)
$m_{tare\ EV}$	EV tare weight	kg	2,940	Workhorse (2020)
$m_{tare\ UAV}$	Drone tare weight without battery	kg	8	Interview
$Z_{batt\ truck}$	Truck battery energy density	kWh/kg	0.15	Kirschstein (2020)
$Z_{batt\ drone}$	Drone battery energy density	kWh/kg	0.26	Interview
$Cap_{batt\ truck}$	Usable truck battery capacity	kWh	105	Workhorse (2020)
$Cap_{batt\ drone}$	Nominal drone battery capacity	kWh	0.8	Interview
$n_{batteries\ per\ drone}$	Number of batteries per drone		2	Interview
MDR	Maximum Discharge rate for LI ION batteries	%	80	Stolaroff et al. (2018)
UL_{truck}	Useful life for trucks	years	10	Yang et al. (2018)
UL_{drone}	Useful life for drones	years	5	Interview

Table B2
Input value for end-of-life phase.

Description	Value (as % of production phase emission reduction)	Source
CO2e savings from vehicles' body recycling	−17%	Lee et al. (2013)
CO2e savings from Li-Ion batteries recycling	−19%	Sullivan and Gaines (2012)

Appendix C. Use Phase Model and Values

See Tables C1, C2, C3,C4, C5, C6.

Table C1
Formulas for drone energy consumption model.

Description	Formula
Power needed to counteract the drone body air drag	$P^{air} = \frac{1}{2} \cdot \rho \cdot v_d{}^3 \bullet A_{drone} \bullet c_{airdrone}$
Power to lift the drone	$P^{lift} = w \bullet k \bullet (\sqrt{m^2 \bullet g^2 + D^2} + 2 \bullet D \bullet m \bullet g \bullet v_d \bullet sin\gamma)$
Air Drag coefficient	$D = \frac{1}{2} \bullet \rho \bullet v_d{}^2 \bullet A_{drone} \bullet c_{airdrone}$
Downwash coefficient	w can be computed solving the following: $\frac{T}{2 \bullet \rho \bullet r^2 \bullet \pi \bullet n_{rotors}} = w \bullet \sqrt{(w - v_d \bullet sin\alpha)^2 + (v_d \bullet cos\alpha)^2}$
Angle of attack	$\alpha = \arctan(\frac{-D - m \bullet g \bullet sin\gamma}{m \bullet g \bullet cos\gamma})$
Power needed to counteract the rotors' air drag	$P^{profile} = \rho \bullet r^2 \bullet \pi \bullet n_{rotor} \bullet v_r{}^3 \bullet \left(1 + 2 \bullet \left(\frac{v_d}{v_r}\right)^2\right) \bullet \vartheta \bullet \frac{c_{bd}}{8}$
Rotor speed	$v_r = \frac{6 \bullet m \bullet g}{n_{rotor} \bullet n_{blades} \bullet c_{mean} \bullet c_{l\_mean} \bullet \rho \bullet r}$
Disc solidity ratio	$\vartheta = \frac{n_{blades} \bullet c_{mean}}{\pi \bullet r}$
Power needed to climb	$P^{climb} = m \bullet g \bullet v_d \bullet sin\gamma$

Table C2
Formulas for vehicles energy consumption model.

Description	Formula
Power needed to counteract the drone body air drag	$P^{air} = \frac{\rho \bullet c_{airtruck}}{2000} \bullet A_{vehicle} \bullet v_t{}^3$
Power needed to counteract rolling resistance, the gravity force in case of sloped road	$P^{roll} = g \bullet c_{roll} \bullet v_t \bullet m$
Power needed to counteract the gravity force in case of sloped road	$P^{grade} = g \bullet i \bullet v_t \bullet m$
Power needed to counteract the inertial force	$P^{inert} = \frac{n_{acc} \bullet 0.504}{2000 \bullet 3.6} \bullet v_t{}^3 \bullet m$

Table C3
Input values for drone energy consumption model.

Abbreviation	Description	Unit of measure	Value	Source
A_{drone}	Frontal surface area	m^2	0.2	Interview
$v_{d\ (level\ flight)}$	Drone speed during level flight	m/s	17	Interview
$v_{d\ (takeoff\ and\ landing)}$	Drone speed during takeoff and landing	m/s	2.3	Interview
P^{int}	Power internal auxiliaries	kW	0.1	Kirschstein (2020)
ε_{eng}	Engine efficiency		0.9	Kirschstein (2020)
ε_{trans}	Transmission efficiency		0.9	Kirschstein (2020)
ε_{char}	Charging efficiency		0.9	Kirschstein (2020)
n_{rotor}	Number of rotors		8	Interview
n_{blades}	Number of blades		2	Interview
r	Rotor radius	m	0.23	Interview
$c_{air\ drone}$	Air drag		0.5	Kirschstein (2020)
c_{bd}	Blade drag		0.075	Kirschstein (2020)
c_{mean}	Rotor mean chord		0.1	Kirschstein (2020)
c_{l_mean}	Blade lift		0.4	Kirschstein (2020)
k	Lifting power mark-up		1.15	Kirschstein (2020)
ρ	Air density	kg/m^3	1.225	–
$m_{payload}$	Weight of the payload	kg	2.5	Kirschstein (2020)
a	Altitude reached by the drone	m	60	Interview
γ	Descent and ascent angle	degrees	90	Interview
t_{hover}	Time for hovering	s	30	Xu (2017)

Table C4
Additional notations used in the drone energy consumption model.

Abbreviation	Description	Unit of measure	Expression
t_{tol}	Time for takeoff and landing	s	$\frac{a}{v_{lf\bullet\sin\gamma} - v_{wind}}$
v_d	Drone speed	m/s	Depending on the drone journey phase, it can be the speed during level flight or the speed during takeoff and landing
t_{lf}	Time for level flight	s	$\frac{d_d}{v_{lf} - v_{wind}} - 2 \bullet t_{tol}$
m	Overall mass of the drone	kg	$m_{tare\ without\ battery} + Cap_{batt\ drone}/Z_{batt} + m_{payload}$
v_{wind}	Wind speed	m/s	Discussed in the sensitivity analysis
t_d	Average drone flight distance between two consecutive truck stops	s	$t_{tol} \bullet 2 + t_{lf} + t_{hover}$
t_w	Drone waiting time (difference between the truck time between two consecutive stops and the drone one)	s	$\frac{d_t}{v_t} - t_d$

Table C5
Input values for the ground vehicles energy consumption model.

Abbreviation	Description	Unit of measure	Value	Source
A_{truck}	Frontal Surface Area	m^2	6	Kirschstein (2020)
C_{roll}	Rolling Resistance		0.008	Kirschstein (2020)
$c_{air\ truck}$	Air Drag		0.65	Kirschstein (2020)
eff_{engine}	Engine Efficiency		0.9	Kirschstein (2020)
eff_{trans}	Transmission Efficiency		0.9	Kirschstein (2020)
eff_{char}	Charging Efficiency		0.9	Kirschstein (2020)
f_{full}	Fuel Consumption (full)	1/h	1	Kirschstein (2020)
f_{idle}	Fuel Consumption (idle)	1/h	25	Kirschstein (2020)
P	Engine nominal power	kW	140	Mercedes-Benz Vans (2020)
n_{acc}	Acceleration frequency coefficient		Discussed in the sensitivity analysis	

Table C6
Input parameter for the Electricity and Fuel Supply Chain Emissions.

Parameter	Unit of Measure	Value	Source
Loss transmission and distribution IT	%	0.97	World Bank (2018)
Fuel emission coefficient WTW	kg CO2/liter	3.24	Schmied and Knörr (2012)

Appendix D. Energy Production Mix

See Table D1.

Table D1
Energy Production mix Values.

Parameter	Unit of Measure	Value	Source
C02e $_{emission\ intensity\ FR}$	g CO2/KWh	58.5	EEA (2018) referring to year 2016
C02e $_{emission\ intensity\ DE}$	g CO2/KWh	440.8	EEA (2018) referring to year 2016

Appendix E. TCO CAPEX Values

See Table E1..

Table E1
Capital Expenses Input Values.

Parameter	Conservative Scenario	Optimistic Scenario	Future Scenario	Source
Electric Van Cost	60,000 €	55,000 €	50,000 €	Assumption
Diesel Van Cost	46,229 €	46,229 €	46,229 €	Mercedes-Benz Vans (2020)
Drone cost	20,000 €	15,000 €	10,000 €	Doole et al. (2020) and Interview
Change of van battery	10,910 €	5,455 €	5,455 €	Doole et al. (2020)

Appendix F. TCO OPEX Values.
See Table F1.

Table F1
Operating Expenses Input Values.

Parameter	Unit of Measure	Conservative Scenario	Optimistic Scenario	Future Scenario
Fuel Cost	€/liter	1.226	1.226	1.226
Electricity Cost	€/kWh	0.195	0.195	0.195
Battery Cost	€/kWh	175	87.5	43.75
Drone Maintenance Cost	€/year	1,710	427	142
DV Maintenance Cost	€/km	0.041	0.041	0.041
EV Maintenance Cost	€/km	0.021	0.021	0.021
Truck Insurance Cost	€/year	600	600	600
Drone Insurance Cost	€/year	1000	500	100
Driver (or Pilot) salary	€/hour	13.9	13.9	13.9
Airspace Cost	€/hour	2	0.5	0.25

Appendix G. Energy consumptions.
See Tables G1 anf G2.

Table G1
Energy Consumption of each vehicle alternative.

Scenario			**Wind speed**		**Density**		**Traffic**		**Energy consumption**				
Conservative	Optimistic	Future	Low	High	Low	High	Low	High	DV [1]	EV [1]	Drone level flight (present paper)[2]	*Drone level flight (Kirschstein, 2020)[3]*	Exemplary drone 1 km flight (present paper)[4]
x			x		x		x		**1.129**	**539**	**66**	***35***	**233**
	X		x		x		x		0%	0%	0%	*0%*	0%
		X	x		x		x		0%	0%	0%	*0%*	0%
x				**X**	x		x		0%	0%	+167%	*+129%*	+58%
x			x			**X**	x		+1%	+2%	0%	*0%*	0%
x			x		x			**X**	+60%	+83%	0%	*0%*	0%

1 = measured in Wh/km.
2 = drone level flight energy consumption [Wh/Km].
3 = drone level flight energy consumption from Kirschstein (2020), computed by Zhang et al. (2021) [Wh/Km].
4 = exemplary 1 km drone flight energy consumption, including takeoff and landing [Wh].

Table G2
Use phase energy requirement per delivery for each alternative.

Scenario			Wind speed		Density		Traffic		Energy consumption per delivery [Wh/delivery]		
Conservative	Optimistic	Future	Low	High	Low	High	Low	High	DV	EV	EV & Drone
x			x		x		x		**2.019**	**963**	**771**
	X		x		x		x		0%	0%	−1%
		X	x		x		x		0%	0%	−1%
x				**X**	x		x		0%	0%	+8%
x			x			**X**	x		−62%	−61%	−58%
x			x		x			**X**	**+60%**	+83%	+78%

Appendix H. Emissions breakdown per scenario for each last-mile logistics combination.

Scenario			**Wind speed**		**Density**		**Traffic**		**Energy prod. mix**		**Use phase emissions [gCO2e/delivery]**			**Production and recycling phase emissions [gCO2e/ delivery]**			**Overall LCA emissions [gCO2e/delivery]**		
Conservative	Optimistic	Future	Low	High	Low	High	Low	High	High	Low	DV	EV	EV + UAV (n = 1)	DV	EV	EV + UAV (n = 1)	DV	EV	EV + UAV (n = 1)
x			x		x		x		x		**654**	**454**	**364**	**75.6**	**221**	**191**	**730**	**675**	**555**
	X		x		x		x		x		0%	0%	0%	0%	−31%	−35%	0%	−10%	−12%
		X	x		x		x		x		0%	0%	−1%	0%	−47%	−52%	0%	−15%	−19%
x				**X**	x		x		x		0%	0%	+8%	0%	0%	+13%	0%	0%	+9%
x			x			**X**	x		x		−62%	−61%	−58%	−33%	−50%	−47%	−59%	−58%	−54%
x			x		x			**X**	x		+60%	+94%	+78%	0%	+65%	+50%	+54%	+84%	+68%
x			x		x		x			**X**	0%	−87%	−87%	0%	0%	0%	0%	−58%	−57%

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