Sustainable Last-Mile Delivery with Autonomous Aerial Vehicles and Autonomous Terrestrial Robots: a Case Study*

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***Abstract*—Last-mile delivery remains one of the key challenges in modern logistics, especially given the growing demand for fast and efficient transport solutions. This study evaluates two delivery strategies: autonomous aerial drone delivery with one parcel per trip and autonomous terrestrial robot delivery with the ability to transport multiple parcels per trip. Simulation modeling is used to analyze the economic, environmental, and social aspects of these methods. The study applies Simulation of Urban Mobility software to simulate the performance of autonomous terrestrial robots in an urban environment taking into account traffic, and a mathematical model to evaluate the performance of autonomous aerial drones. Three scenarios are considered: (1) drone-only delivery, (2) robot-only delivery, and (3) mixed fleet approach combining both methods. The results show that autonomous aerial drones provide faster delivery, but autonomous terrestrial robots are a more economical and environmentally sustainable solution. The hybrid approach strikes a balance between efficiency and cost, optimizing last-mile logistics. This study contributes to the development of sustainable urban delivery models and provides practical recommendations to policy makers and logistics companies.**

I. Introduction

Last-mile delivery poses one of the most significant challenges in modern logistics, especially with the rapid growth of e-commerce and urbanization. The use of autonomous drones as a delivery method has opened new opportunities to optimize logistic processes: reducing road congestion, reducing carbon emissions, and accelerating delivery times. However, numerous challenges remain, particularly in determining the most efficient delivery operation model.

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The integration of advanced technologies into logistics systems has brought about significant advancements, but also introduced complexities that require careful study. Swanson [1] proposed a simulation-based model to minimize the total delivery time by optimizing drone fleet operations, demonstrating the potential of drones in dense urban environments. Similarly, Verri *et al.* [2] analyzed tradable permit models, offering solutions for equitable and efficient airspace allocation among drone operators. These works highlight the need for effective regulatory and logistical frameworks to maximize the benefits of drone delivery systems. Eeshwaroju *et al.* [3] further advanced this area with the IoT-based Three-Dimensional Dynamic Drone Delivery system, which uses IoT integration for real-time route adjustments, enhancing operational efficiency.

Several studies have explored the integration of different transport modes to improve the efficiency of delivery. Gerrits and Schuur [4] proposed a synchronization approach combining drones, trucks, and street robots for parcel delivery in smart cities, focusing on coordinated operations to reduce delivery time and resource wastage. Similarly, Wang *et al.* [5] introduced a hybrid delivery model using drones and electric trucks, demonstrating significant reductions in carbon emissions and delivery costs through effective collaboration. These findings emphasize the potential benefits of combining various delivery methods, which is critical when evaluating robots and drones in last-mile logistics.

Energy efficiency remains a critical aspect of logistics. Bruni *et al.* [6] developed energy-efficient unmanned aerial vehicle models that incorporate non-linear energy consumption to improve operational sustainability while reducing costs.

Furthermore, Liu *et al.* [7] highlight strategies for optimizing energy consumption using mixed fleets, which is crucial for evaluating the sustainability of drones and robots. Qu *et al.* [8] explored environmentally aware robotic vehicle networks, which provide energy management strategies supporting green logistics. In addition, Atiyah *et al.* [9] propose a methodology to improve energy efficiency in wireless systems, which can be adapted for last mile logistics.

Based on the analysis of the related literature, this paper aims to address the gap in comparing single-package delivery autonomous aerial drones with autonomous terrestrial robots capable of carrying multiple packages per trip [10]. The logistic performance of urban vehicles can be simulated with specific software developed according to the requirements of the environment to be analyzed [11]. The study applies Simulation of Urban Mobility (SUMO) software to simulate the performance of autonomous terrestrial robots in an urban environment taking into account traffic, and a mathematical model to evaluate the performance of autonomous aerial drones. Three scenarios are considered: (1) drone-only delivery, (2) robot-only delivery, and (3) mixed fleet approach combining both methods. The results show that autonomous aerial drones provide faster delivery, but autonomous terrestrial robots are a more economical and environmentally sustainable solution. The hybrid approach strikes a balance between efficiency and cost, optimizing last-mile logistics. The findings will help determine which approach is more effective in terms of economic, social, and environmental performance.

The remainder of this paper is the following. Section II presents the methodology used to compare the proposed last-mile deliveries. Section III describes the case study and Section IV discusses the results. Finally, Section IV reports conclusions and future research.

II. Methodology

This study employs a comparing approach to evaluate the performance and efficiency of delivery systems involving an autonomous terrestrial robot and an autonomous aerial drone. The methodology consists of two key phases: (1) simulating the autonomous terrestrial robot's operations using SUMO and calculating the autonomous aerial drone's performance through a mathematical model; (2) developing and analyzing different operational scenarios to compare their effectiveness. The first phase of the methodology involves modeling the autonomous terrestrial robot's operations in the SUMO environment. SUMO is an open-source software for microscopic traffic flow simulation that provides a detailed and controlled platform for studying transportation systems. By leveraging the capabilities of SUMO, the study records key performance metrics of the autonomous terrestrial robot, including the total distance traveled and the time spent on completing predefined delivery tasks. The simulation replicates real-world conditions, allowing for an accurate assessment of the autonomous terrestrial robot's capabilities in dynamic delivery scenarios.

Unlike an autonomous terrestrial robot, the performance of an autonomous aerial drone is not simulated but rather analyzed using a mathematical model, since autonomous aerial drones do not face traffic problems. Therefore, their performance was assessed using a mathematical model rather than simulation. This model provides estimates of critical performance parameters such as total flight range, total delivery time, and the number of autonomous aerial drones required to complete all deliveries within the allotted operating hours. This approach provides a structured and objective assessment of drone performance based on predefined conditions. To assess the performance of drone-based delivery, a mathematical model is developed to estimate the total flight distance, total delivery time, and the minimum number of drones required to complete all deliveries within the available working hours. The total flight distance covered by all drones in one day is given by Equation (1):

$$L_{\text{total}} = \sum_{i=1}^{n} N_{C_i} \cdot 2 \cdot (D_i + d_{t_l}) \tag{1}$$

where:

- n is the number of delivery departments,
- N_{C_i} is the number of customers in department i,
- D_i is the hub-to-department distance,
- d_{t_l} is the take-off and landing distance of the drone.

The constant equal to 2 in Equation (1) is included to take into account the outbound and return trips.

The total time required to complete all deliveries, considering both flight time and service time, is calculated using the following equation.

$$T_{\text{total}} = \sum_{i=1}^{n} N_{C_i} \left(\frac{2D_i}{v} + 2T_{t_l} + T_c \right) \tag{2}$$

where:

- $\frac{2D_i}{v}$ represents the round-trip flight time from hub-to i-th department,
- $2T_{t_l}$ is the time required for the drone's take-off and landing,
- T_c is the service time required to deliver the package to the customer,
- v is the average speed of the drone.

To ensure that all deliveries are completed within the available working hours, the required number of drones is determined by the following formula:

$$Q'_{\text{drones}} = \left\lceil \frac{T_{\text{total}}}{T_w} \right\rceil \tag{3}$$

where:

- T_w is the total available working time per day (minutes)

By combining Equation (1), (2) and (3), the complete formula for estimating the required fleet size is the following:

$$Q'_{\text{drones}} = \left\lceil \frac{\sum_{i=1}^{n} N_{C_i} \left(\frac{2(D_i + d_{t_l})}{v} + 2T_{t_l} + T_c \right)}{T_w} \right\rceil \tag{4}$$

Formula (4) provides an estimation of the number of drones necessary to complete all deliveries within the given operational constraints.

In real-world applications, drone operations may also be subject to regulatory constraints such as visual line-of-sight requirements, altitude limits, and restricted flight zones. While these aspects are not explicitly modeled in this study, they represent important operational constraints to consider in practical implementations.

A. Sustainability Key Performance Indicators

Sustainability key performance indicators are a useful tool for comparing urban mobility solutions [12]. The efficiency of autonomous aerial drone-based and autonomous terrestrial robot-based delivery, is evaluated by considering the following key performance metrics:

1) **Total delivery time:** calculated for each strategy.
2) **Total number of trips:** determined for each zone.
3) **Required number of drones and robots:** calculated based on the available working hours per day.
4) **Distance traveled daily and annually:** measured for both strategies.
5) **Environmental, social and economic aspects:** analyzed based on the results from the mathematical model and SUMO simulations.

The sustainable evaluation is based on the analysis of environmental and social impacts by calculating the cost of externalities between the different strategies, to compare the economic effectiveness.

The autonomous aerial drone model is defined by several key parameters. Autonomous aerial drone speed is considered in the analysis, as it is necessary to calculate the time required for deliveries based on the type of vehicle. The service time per client represents the time needed for the drone to complete the handover of a parcel. The payload capacity is limited to a single parcel per trip, meaning that each autonomous aerial drone can carry and deliver only one package at a time. The working time refers to the number of hours the vehicle operates within a defined work schedule. Similarly, the autonomous terrestrial robot model follows the same structure. Autonomous terrestrial robot speed is used to determine delivery time depending on the type of vehicle. The service time per client remains the same as for drones. Unlike autonomous aerial drones, the payload capacity of the autonomous terrestrial robot allows for multiple parcels per trip, enabling more efficient batch deliveries. The working time is also determined by a fixed work schedule.

III. Case Study

To evaluate the proposed methodology in a real-world scenario, the Polytechnic University of Bari (Italy) was chosen as a case study. The delivery process involves transporting parcels from a central distribution hub to nine departments, each one with a unique number of clients and distance from the hub (Fig. 1).

Fig. 1. Map of the Polytechnic University of Bari

This example allows us to analyze the efficiency of three delivery strategies: single-parcel delivery by an autonomous aerial drone per trip and multiple parcels delivery by an autonomous terrestrial robot per trip, mix fleet with autonomous aerial drone and autonomous terrestrial robot. For the purposes of this study, it is assumed that 12 clients are served in each department, for a total of 108 clients per day, and that the autonomous terrestrial robots have a maximum capacity of three parcels per trip. The other parameters considered for the comparative analysis are described below.

The drone model includes the following key input parameters:

1) **Drone speed:** 30 km/h (500 m/min).
2) **Service time per client:** 2 minutes per client.
3) **Payload capacity:** One parcel per trip.
4) **Working constraints:** 8-hours workday and 220 working days per year.

The robot model includes the following key input parameters:

1) **Robot speed:** 8 km/h (2.22 m/min).
2) **Service time per client:** 2 minutes per client.
3) **Payload capacity:** Three parcels per trip.
4) **Working constraints:** 8-hours workday and 220 working days per year.

The key input parameters for drone and robot models are summarized in Table I.

TABLE I
KEY INPUT PARAMETERS FOR DRONE AND ROBOT MODELS

Parameter	Drone	Robot
Speed	30 km/h (500 m/min)	8 km/h (2.22 m/min)
Service Time per Client	2 minutes	2 minutes
Payload Capacity	1 parcel	3 parcels
Working Hours per Day	8 hours	8 hours
Operating Days per Year	220 days	220 days

A. Scenarios

This study analyzes three delivery scenarios to evaluate their efficiency within a case study framework.

The first scenario involves single-parcel delivery, where each drone performs a separate trip to deliver one parcel. In this case, each client requires an individual trip from the central hub to their location. The total number of trips is directly proportional to the number of clients in each department. The total delivery time is calculated as the sum of flight time, take-off and landing time, and service time for all clients, while the total distance includes the round-trip distance from the hub to each client. This approach simplifies operational planning, as each trip serves only one client, making it particularly effective in low-density areas where clients are widely distributed across the territory. However, the drawbacks of this scenario include higher operational costs, increased energy consumption, and longer delivery times due to the larger number of required trips.

The second scenario involves multiple parcel delivery, where a robot can deliver up to three parcels per trip. In this case, the total number of trips is significantly reduced as each trip serves multiple clients. The total delivery time takes into account additional stops and service time for each client. The total distance includes routes from the hub to the group of clients and the distances between clients within a single trip. This scenario is more efficient in high- density delivery zones, where clients are located closer to each other, as it reduces the total delivery time and overall distance traveled.

The third scenario involves the collaboration of autonomous aerial drones and autonomous ground robots, which simultaneously deliver packages from a hub directly to customers. In this model, drones are used for short-range deliveries, ensuring fast transportation of packages to nearby customers, while robots perform longer-range deliveries, effectively covering large areas. This distribution of tasks allows for a significant reduction in both the overall delivery time and the distance traveled by each type of transport. As a result, the hybrid approach will reduce operating costs and energy consumption, increasing the overall efficiency of last-mile logistics. This system is an effective solution for sustainable urban logistics.

B. Model for autonomous aerial drones

The drone flight paths were modeled as direct routes from the hub to the department without taking into account the extensive waypoint optimization. In practice, drones must perform vertical takeoffs and landings and occasionally adjust their flight paths to comply with airspace regulations and safety corridors. These additional maneuvers increase the overall distance traveled compared to purely ground-based routes. Therefore, the longer distances recorded for drones in Table I correspond to realistic drone operating conditions.

The last mile delivery performed with the use of autonomous aerial drone to serve all 108 clients, achieved the following results:

- **Total distance traveled:** 96,000 meters.
- **Total delivery time:** 408 minutes.
- **Number of drones required:** Only one drone was needed to complete all deliveries within the given constraints.

These results confirm that a single drone is capable of completing all deliveries within the available working hours while adhering to the defined operational constraints.

C. Autonomous terrestrial robot simulation

The robot simulation was carried out in SUMO, which provided a detailed and dynamic environment to analyze robot-based delivery operations, ensuring results as close to real world conditions as possible. SUMO allows the incorporation of various factors to calculate not only the required time but also the distance traveled by the robot (Fig. 2).

The simulation considers traffic consisting of 100 motorcycles per hour, 100 bicycles per hour, and 600 pedestrians per hour. Since two of the delivery points are located outside the campus of the Polytechnic University of Bari, the robot is required to cross both a pedestrian crossing and a roadway. In this area, the traffic also includes 500 cars per hour, 150 buses per hour, and 50 trucks per hour, along with the previously mentioned pedestrians, bicycles, and motorcycles.

Although two delivery points are located outside the main campus and require crossing the road, these crossings occur at pedestrian crossings without traffic lights. Therefore, the additional waiting time at signalized intersections was not taken into account when calculating delivery times.

The robot is capable of delivering three parcels per trip, after which it returns to the hub to collect the next batch. A total of 9 departments need to be served, following the same algorithm: pick up three parcels from the hub, deliver them to clients, and return for the next batch. This process continues until all deliveries are completed. Such an approach ensures efficient parcel distribution, optimizing both travel distance and delivery time within an urban environment.

Such an approach ensures efficient parcel distribution, optimizing both travel distance and delivery time within an urban environment. The results of the SUMO simulation provided detailed data on how many kilometers the robot traveled each day and how much time was required to complete all deliveries, considering real traffic conditions. Based on the SUMO simulation, servicing all 108 clients required, the results are:

- **Total distance traveled:** 36,426 meters.
- **Total delivery time:** 564.2 minutes.
- **Number of robots required:** Two robots were needed to complete all deliveries within the constraints given.

Since this exceeds the available 480-minutes workday, an additional robot is required to complete all deliveries within the given constraints. This highlights the impact of real-world traffic conditions on delivery efficiency, emphasizing the need for multiple robots to ensure timely delivery under operational constraints.

As shown in Table II, the travel distances for autonomous aerial drones and autonomous terrestrial robots vary significantly depending on the department.

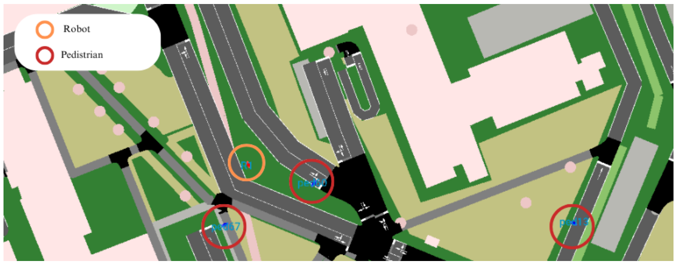

Fig. 2. Simulation of robots in SUMO

TABLE II
TRAVEL DISTANCES FOR ROBOTS AND DRONES

Department	Robot by SUMO (m)	Drone (m)
DMMM	64.42	200
DEI	73.35	250
ArCoD	99.1	300
DSTG	290.69	350
Math	349.67	400
DFSF	440.23	450
Agraria	501.1	500
Amministrazione	739.8	600
LabZERO	1000	700

IV. RESULTS

This section evaluate economic, social and environmental performance of the proposed methodology.

The economic factor are based on investment costs, energy costs, depreciation period (in years), and insurance. It is also important to consider the number of workers and their daily wage, as well as maintenance costs, which contribute to the overall operating costs.

In this study, we supposed an energy price of 0,30 dollars/kWh, annual insurance is equal to 10 percent of the cost of the vehicles, hourly worker cost (involved in the delivery activities through carrying of package in the autonomous vehicles) is 38 dollars and annual maintenance cost equal to 2,000 dollars for each vehicle. Economic values are calculated by also considering data on annual mileage (Year travel distance), number of drones and robots needed, and total delivery time. These values are obtained by the mathematical calculation and simulations performed in the previous section for each scenario. In the first scenario, only one autonomous aerial drone is needed because the total delivery time is less than the available working time. While in the second scenario, two autonomous terrestrial robots are needed, as the delivery time exceeds the available working time. In the third scenario one autonomous aerial drone and one autonomous terrestrial robot are able to complete all deliveries in a working day. The autonomous terrestrial robot is responsible of customers located in denser areas where its ability to carry multiple packages per trip maximizes efficiency. The autonomous aerial drone is being used to increase performance in delivering packages to much more distant customers, to reduce total delivery time.

The investment and operational costs considered in the economic analysis are summarized in Table III.

TABLE III
INVESTMENT AND OPERATIONAL COSTS FOR VEHICLES

Cost Item	Drone	Robot
Purchase Cost (USD)	5,000	5,500
Annual Maintenance Cost (USD)	2,000	2,000
Annual Insurance Cost (USD)	500	550
Energy Price (USD/kWh)	0.30	0.30
Worker Cost (USD/hour)	38	38
Depreciation Period (years)	5	5

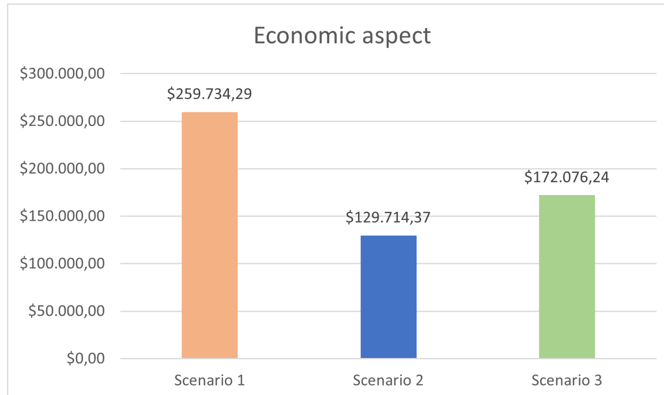

Fig. 3. Economic aspect for each scenario

Figures 3, 4, and 5 provide a comparative analysis of the three delivery scenarios across economic, environmental, and social dimensions. Specifically, Figure 3 presents the total operational costs for each delivery model. Figure 4 illustrates the environmental impact measured in terms of CO_2 emissions resulting from energy consumption. Figure 5 shows the social impact, considering noise pollution and accident risks associated with each delivery solution.

The economic results obtained from this analysis for each scenario are presented in Figure 3.

The results of the analysis clearly show that the most economically advantageous option is delivery using robots. This conclusion is based on a comparative analysis of the total costs for each scenario, where robotic delivery demonstrated the greatest cost effectiveness by reducing labor and energy costs while maintaining operational feasibility. While a hybrid approach involving both drones and robots can balance the load and optimize delivery times.

The environmental impacts are linked to air pollutant emissions, considering the electric powertrain used. Externalities considered for this factor are based on the transport external costs proposed in EU Handbook [13]. As shown in Figure 4, we can see the environmental aspect for each scenario.

The analysis takes into account the emissions resulting from energy consumption, the impact on climate change, and the total distance traveled by each mode of transport. This data allows for a comprehensive comparison of the sustainability of different operating models and the most environmentally friendly and cost-effective solution for urban logistics. Here, too, we see the superiority of the robot-only scenario.

The social impacts considered are related to noise pollution

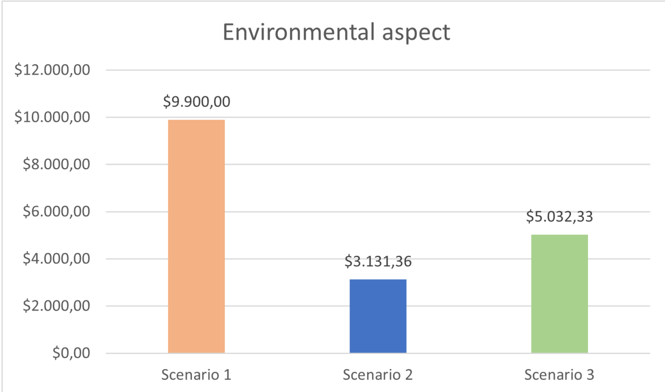

Fig. 4. Environmental aspect for each scenario

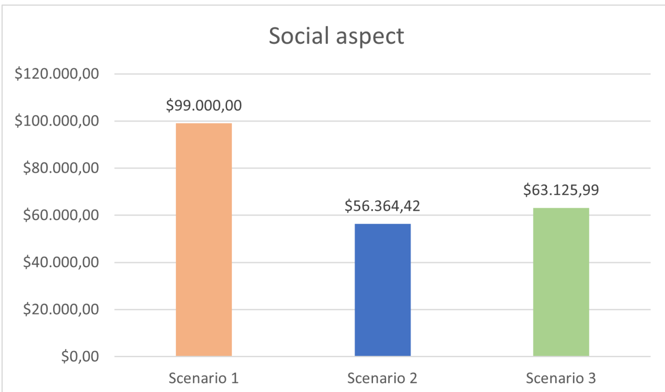

Fig. 5. Social aspect for each scenario

and accidents. Externalities considered for these factors are derived by similar vehicles described in the transport external costs proposed in EU Handbook [13].

Figure 5 presents the results of this analysis, showing how different delivery models affect social aspects such as urban noise levels and accident risks.

Although robots exhibit higher accident risk due to interaction with ground traffic, they generate lower noise levels compared to drones. Conversely, drones minimize collision risks but contribute to greater noise pollution. Therefore, the results are affected by the urban density and community sensitivity in which to use the two last mile delivery options.

V. Conclusion

In this paper, a comparative analysis of sustainable urban delivery models is performed considering autonomous aerial drones and autonomous terrestrial robots. Three scenarios were developed using: i) only drones with only one transportable package per trip, ii) only robots with multiple transportable packages per trip, and iii) a mixed fleet with drones and robots. Distances and relative times in drones' delivery were calculated and robots was simulated to obtain distances and times as close to real situations as possible, given the presence of other vehicles on the roads.

The comparative analysis on the environmental, economic, and social sustainability is adopted to evaluate the different scenarios developed in innovative last-mile delivery activities. The assessment uses external costs to evaluate the differences in social and environmental impacts through analysis of air pollution, noise pollution, and accidents. In addition, a cost analysis approach is adopted to identify the economic value considering investment and operative costs.

A case study was developed to assess the potential and compare the impacts of different approaches.

In future work, we plan to extend the proposed framework by introducing dynamic routing strategies based on real-time traffic and demand data.

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