22nd *International Conference on Modelling and Applied Simulation*
20th International Multidisciplinary Modeling & Simulation Multiconference

2724-0037 © 2023 The Authors.
doi: 10.46354/i3m.2023.mas.006

Simulation modelling for integrating economic and environmental performance assessment for autonomous delivery systems in last mile logistics.

Lorenzo Rubrichi[1,*], Maria Grazia Gnoni[1] and Fabiana Tornese[1]

[1]Department of Innovation Engineering, University of Salento, Campus Ecotekene, Lecce, Italy

[*]Email addresses: lorenzorubrichi@gmail.com, mariagrazia.gnoni@unisalento.it, fabiana.tornese@unisalento.it

Abstract

Last mile logistics represents one of the most complex tiers in the current supply chains due to several different factors, among these are the increasing diffusion of e-commerce and customer touchpoints. Moreover, pollution problems in urban areas as well as traffic congestions represent another critical issue. The adoption of smart (unmanned delivery systems) and sustainable (electric vehicles) technologies for delivery could be a promising option. Electric vehicles could allow for a reduction in environmental and noise pollution, as well as energy savings. Unmanned vehicles (drones and delivery robots) can lead to a reduction in the manpower cost and vehicle life cycle management. Some studies have been published about the potential adoption of these smart technologies in last mile logistics. In this paper, after a general overview of the introduction of unmanned delivery systems in last mile logistics, an agent-based simulation of a last mile delivery system in an Italian urban area is proposed. The model allows to compare mixed and single delivery system scenarios trough an integrated set of KPIs in order to assess economic and environmental performance. Results derived from the test case development show integrated performance of different delivery systems that could be applied in last mile logistics.

Keywords: Last Mile Logistics, Unmanned Delivery system, Economic Performance, Environmental Performance

1. Introduction

The last mile delivery is a critical and complex aspect of the supply chain, which involves the transportation of goods from distribution centres or fulfilment hubs to the final destination, typically the end consumer. The traditional methods of last mile logistics, heavily dependent on human-driven vehicles, are often associated with inefficiencies (Mangiaracina et al., 2019), high expenses (Pina-Pardo et al., 2022) and negative environmental consequences (Manerba et al., 2018). But recent advances in drone and delivery robot technology have opened up new ways to improve the last mile delivery process.

Anylogic facilitates the development of virtual environments that resemble real-world scenarios. This allows researchers, technologists, and policymakers to assess the effectiveness and viability of various operational strategies, evaluate the impact of various variables, and make informed choices before implementing them in the real world (Borshchev, 2013).

The purpose of this paper is to investigate the use of computer simulation software to re-create and examine the last mile delivery procedure involving drones and robotic delivery vehicles. We explore how to build simulation tools that accurately replicate the behaviour of real-world scenarios, considering factors like geographical limitations, traffic patterns, customer demand, and operational constraints specific to drones and delivery robots.

This paper includes the following elements: a comprehensive literature review in section 2; scenarios to be evaluated in section 3. Section 4 introduces the simulations model realized with Anylogic. Results and a discussion are presented in section 5. The conclusion and suggestions for further investigation are summarized in section 6.

2. State of the art

The debate surrounding the introduction of autonomous delivery systems has gained increasing interest recently, with several studies proposing delivery systems based on unmanned aerial delivery vehicle (UADV) (Rodrigues et al., 2022)(Lamb et al., 2022), on autonomous delivery robot (ADR) systems (Madani & Ndiaye, 2019)(Sindi & Woodman, 2020) and on the integration of these two systems with the traditional delivery system based on vans or trucks (Liu et al., 2022)(Tiniç et al., 2023).

The examination of the available literature revealed a set of goals that the application of simulation tools to the investigation of unmanned delivery systems in the field of last-mile logistics aims to achieve. These objectives are focused on increasing delivery range, improving flight safety, reducing delivery times, optimizing costs, and reducing the environmental impact of the current last mile delivery system.

2.1. Battery management to increase delivery range

As autonomous vehicles are powered by electricity, capacity of the battery is closely associated with the delivery range. Due to this reason, some studies focus on the optimal deployment and management of vehicles to optimize the utilization of batteries and attain greater ranges.

For example, studies show that drone stations can be used to charge or replace batteries in UAVs to increase their range. (Cokyasar et al., 2021) uses the planning and operations language for agent-based regional integrated simulation (better known as POLARIS) and proposes a network design that uses automated battery swapping machines (ABSMs) to increase the maximum reachable distance. (Huang et al., 2022), also suggests 4 ways to get greater ranges and deliver over long distances. The study in question uses a computer-based experiment to show the effectiveness of the proposed approaches in terms of delivery times. The study of (Utomo et al., 2022) using agent-based simulation aims to investigate a home food delivery system using electric vehicles or ADR. The model in question aims to determine the optimal fleet of vehicles and the size of the batteries, introducing the concept of a heterogeneous fleet. The deployment of a fleet of unmanned vehicles and batteries of different capacity has led to economic benefits.

2.2. Unmanned vehicles safety

In terms of safety, simulations aim to increase flight precision and control of the delivery area to allow delivery directly to the balcony or a room, avoiding collisions. In (Chen et al., 2022) and (Brunner et al., 2019) studies testing UAV delivery systems that simultaneously integrate the GPS system to allow the drone to reach the delivery point, and visualization tools to proceed accurately and avoid collisions, during package delivery. Similarly, (Seo & Jung, 2023)present a study to test the effectiveness of anti-collision systems and a classification of the different types of collisions as well for ADR delivery systems.

2.3. Delivery Time

Another common objective in the literature examined is to demonstrate through simulation how the use of unmanned systems in last mile can significantly shorten delivery times. In (Babu et al., 2022), an agent-based simulation in Anylogic software is used, where conventional delivery trucks are supplemented with automatically couplable trailers. The possibility of autonomous pick-up from a trailer placed at a suitable location in the city affects the total duration of the tour, therefore directly reducing delivery times.

Using an agent-based simulation, (Poeting et al., 2019) analyse a delivery system based on conventional vans, implements it with a fleet of ADRs and simulates a series of scenarios to solve the travelling salesman problem. Results have shown how the use of a conventional van + ADR system could improve delivery performance from a scheduling perspective.

Using a discrete event simulation, (Swanson, 2019) analyses a variety of scenarios where one of the following parameters varies: distance, travel speed and processing time, and compares the solution with the traditional delivery lorry and a drone delivery-based system. The results prove in every case that the drone is a better choice compared to the delivery lorry in terms of delivery times.

Regarding the introduction of ADR systems, (Schnieder et al., 2022) proposes a simulation-based decision support method to find the optimal combination of the number of pick-up points and the ADR delivery concept based on the required time range. Reducing the time range for parcel delivery increases the effectiveness of land use in cities, reduces the space required for roads and car parks, and creates more space for housing and parks.

2.4. Cost

Simulation models are also used to find out how to cut costs in unmanned delivery systems. An example is the work of (Imran et al., 2023), which aims to fully automate the last-mile delivery process by utilizing drones. A series of simulated scenarios revealed that a system based on autonomous vehicles (cars and drones) can satisfy all users and minimize the total ownership cost.

The study of (Jackson & Srinivas, 2021) uses a discrete event simulation to evaluate the introduction of 3 delivery systems to deliver medicines directly from pharmacies to end customers in the last mile: Lorry Only, Lorry Drone and Drone Only. The model suggests that a drone-only system is most effective when numerous drones are available.

(Yuan & Herve, 2022) introduces the concept of a transshipment area, which is a fixed area in a city, e.g. a large square or commercial area demarcated by the municipality. The model presented shows through simulations that costs and delivery times obtained with unmanned delivery system can be reduced compared to the traditional delivery system.

2.5. Environmental impact

Dealing with the environmental impact of unmanned delivery systems in last mile logistics, (Khalid & Chankov, 2020) develops the concept of drone delivery using public transport. It explores its potential by comparing it with traditional delivery by lorry, running an agent based simulation on Anylogic software. The simulation results indicate that delivery companies can significantly reduce CO2 emissions by introducing the concept of drones linked to public transport.

Instead, (Gerrits & Schuur, 2021) uses discrete event simulation via the "Plant Simulation" tool to propose a last mile delivery concept where a lorry driver cooperates with a mixed fleet of drones and ADRs in the delivery process. The simulation results show that delivery time and emissions can be drastically reduced when UAV or ADR are used, especially when the driver delivers heavy parcels alongside the unmanned vehicles.

Finally, in a simulation study, (Kirschstein, 2022) compares, through a simulation, a delivery system based on drones with one based on conventional combustion vehicles and one based on electric vehicles. The simulation results prove that drones consume more energy than diesel and electric trucks, especially when customer density is high in relatively small areas. Drones consume comparable or even slightly less energy than trucks in more rural environments with large areas and low customer density, provided wind conditions are calm to moderate.

3. Scenarios to be evaluated

The present study aims to explore three types of scenario related to last-mile logistics (LML) through simulations performed using the Anylogic software. Specifically, these scenarios are: delivery systems based on traditional internal combustion vans (Van), delivery systems based on UADV, ADR-based delivery system. The proposed model therefore envisages the presence of customers who place orders and choose the type of delivery to receive; only customers close enough to the distribution centre can take advantage of unmanned delivery. The distribution centre receives orders at all times, but they are processed only during 8 working hours. Parcels delivered after 8 working hours are processed in overtime, which will therefore see an increase in costs relating to the hourly wage of 20%. Parcels that cannot be delivered within 9 hours (8 plus overtime) will be entrusted to an outsourced delivery, whose cost is defined as 25% higher than a package delivered overtime.

3.1. Performance Indicator definition

The various scenarios analysed possess different characteristics and outcomes, and a set of key performance indicators (KPIs) have been introduced to evaluate the outcomes of the proposed scenarios in the most uniform manner.

- **Time To Customer (TTC):** The time between the moment the package is ready to be shipped, and the distribution centre sends the delivery notification, to the moment the customer receives the order.
- **Delivery rate (DR)**: average number of parcels delivered in one hour. This performance index will be calculated by dividing the number of parcels delivered in the simulated days by the total number of hours each system spent on delivery in the same period.
- **Unit Cost**: Indication that unifies information regarding system performance reported through the number of parcels and the economic information represented by the estimate of total costs in fact the unit cost per parcel is defined by the following equation:

$$UC = \frac{C_T}{N_y}$$

  - N_y: yearly delivery parcels
  - C_T: are total cost defined as follow:

$$C_T = C_p + C_f + C_v + C_{OT} + C_{out}$$

  - C_p: investment cost to purchase vehicle, equipment, backup batteries.
  - C_f: fixed cost for insurance , possession fees, street tolls and operators salaries.
  - C_v: variable cost for energy or fuel purchase
  - C_{OT}: overtime work cost
  - C_{out}: outsourced parcel cost
  -
- **Yearly emissions**: In regard to the estimate of the emissions generated by each delivery system, reference is made only to the emissions relating to last mile delivery, which will be considered by taking the guidelines of the GLEC framework emission. The GLEC protocol includes emissions from the entire life cycle of fuels, known as well To Wheel. This encompasses two subclasses, well to tank (WTT) and tank to wheel (TTW).

Van Delivery emission:

$$EM_{e1} = (Ef_{WTT} + Ef_{TTW}) * \eta * \mathrm{km_y}$$

- $Ef_{WTT} [kg\ CO_2e/l]$: WTT diesel emission factor
- $Ef_{TTW}\ [kg\ CO_2e/l]$: TTW diesel emission factor
- $\eta\ [l/km]$: *vehicle diesel consumption*
- $km_y\ [km]$: *yearly kilometres travelled*

Unmanned Delivery emission:

$$EM_{e2} = Electricity * Ef_e$$

- $Electricity\ [kWh]$: *electricity to yearly delivery*
- $Ef_e\ [kg\ CO_2e/kWh]$: *electricity emission factor*

The KPIs are summarized in Table 1.

Table 1 Key performance indicator.

KPI	Name	M.U.
TTC	Time To Customer	$[h]$
DR	Delivery Rate	$\left[\frac{parcels}{h}\right]$
UC	Unit Cost	$\left[\frac{€}{parcel}\right]$
Em	Yearly emission	$[Kg\ CO_2e]$

3.2. Scenario 1: delivery with VANs

In the analysis relating to delivery with a van, the Volkswagen crafter business 140 hp van was chosen, and information regarding consumption, costs, and emissions was extracted from https://www.volkswagen-veicolicommerciali.it/.

We have defined three values for the traffic level:

- **No traffic**: The average speed is 40 km/h, and the fuel consumption is 12.5 km/l.
- **Medium traffic**: The average speed of medium traffic is 30 km/h, and the fuel consumption level is 11.24 km/l.
- **High traffic**: The average speed of traffic is 20 km/h, and the fuel consumption level is 10.20 km/l.

3.3. Scenario 2: delivery with UADV

In the analysis of a last mile delivery system with UADV the aircraft similar to the one used in the case of https://www.retaildive.com/news/walmart-6000-drone-deliveries-droneup-flytrex-zipline-2022/639837/ where goods are delivered from Walmart supermarkets directly to customers using DroneUp's vehicle. The simulation parameters for a LML with UADVs are as follows:

- Maximum delivery range
- Maximum transportable load
- Movement speed

3.4. Scenario 3: delivery with ADR

Regarding the delivery of parcels in LML with ADR, the example of https://starship.co/ was followed, from where information regarding vehicle performance was extracted. Similar to the evaluation of delivery using drones, the parameters to be evaluated are:

- Maximum delivery range.
- Maximum transportable load.
- Movement speed.

4. Simulation Modelling with Anylogic

The use of modelling is a crucial tool in the process of defining, elucidating, and resolving real-world issues. It has become necessary to introduce this tool because experimenting with the real world would require construction, destruction, and various tests before obtaining results. All of these procedures have the potential to be costly, potentially hazardous, or necessitate prolonged periods of dilation.

For this reason, once a real event has been modelled, simulation is used. Simulation models utilize the modelling of an event or a real system as their input, and produce its trajectory, transformation, and changes over time. Furthermore, simulation models enable the variation of parameters to observe how the model outputs vary with certain parameters. One of the main simulation and modelling software is AnyLogic, which will be used to implement this work. In this case, we will make use of agent-based (AB) and discrete-event (DE) simulation.

The simulation was performed using Anylogic 8.8 software on an HP prodesk computer with Intel(R) Core (TM) i7-7700 CPU 3.60 GHz processor and 16gb of RAM. The simulation covers a month of activity and then the results have been projected on an annual scale.

4.1. Agent: Local Hub

The local hub has been modelled as a single agent, positioned near the DHL distribution hub located in via Taranto in Lecce. The purpose of this agent is to receive the order from the customer and sort it according to the type of delivery required. The agent will also manage the shipment preparation operations (Figure 1).

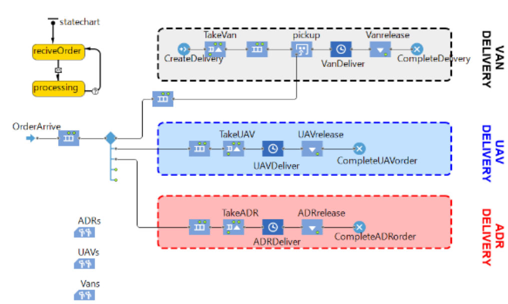

Figure 1 Local hub modelling.

The activities carried out in the local Hub are subject to scheduling which allows activities for a maximum of 9 hours a day (8+1 overtime, if any) and are modelled as follows:

- **Traditional delivery**: the order arrives and sorted in the van delivery department, where the orders wait in queue until they reach a quantity equal to the delivery demand. Once this number is reached, the load will be assigned to a van from the resource pool and the van will leave for the delivery tour. The delay in this process is what stops the process until the van's return signal arrives. Times to leave parcel to customer were chosen at the discretion of the author as variables according to a triangular distribution with minimum 1 minute, maximum 4 and most frequent value 2 minutes.
- **Unmanned Delivery**: in this case the order based on the type of delivery arrives at the department, is assigned to a UADV or an ADR. Similar to the scenario with vans, the process terminates at the point of delay, awaiting the return message from the unmanned vehicle. Take-off and landing times depend on the characteristic speed of the drone, while delivery to the customer by ADR follows a triangular distribution similar to that of the van.

4.2. Agent Customer

The agent named "Customer" is a population of agents, an arbitrary number of agents equal to 3000 people has been defined and placed within the dashed highlighted area as the service area (Figure 2).

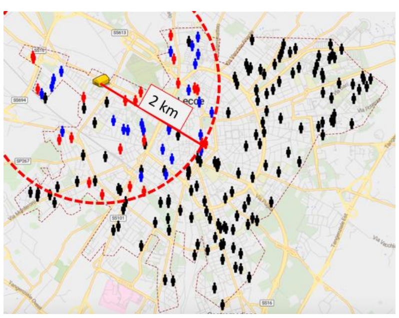

Figure 2 GIS map with customers, orange dotted area is the total serviceable area, circular area is the area reachable by unmanned systems.

The eight different statuses that each customer can have are: delivery request with van, delivery expected with van, delivery request with UADV and request expected with UADV, delivery request with ADR and delivery expected with ADR, return request and finally, customer not present at the moment of delivery. When these agents were introduced, their behaviour was defined as follows: each customer passes from the idle state to the order placed state with a rate of one time per month. In this step, an order is generated which contains information about the customers' position. The Local Hub agent checks the customer's distance from the centre after they place their order. This check uses the parameter "unmanned range" (Figure 2), which is the maximum aerial distance that unmanned systems can reach. If the customer falls outside this range, they can only be served via vans; otherwise, they may opt for a different delivery method.

The choice of delivery system was modelled using choice probabilities (Table 2).

Table 2 Customer delivery preference expressed as probability.

Name	Description
PV	probability that the customer within the "unmanned range" chooses delivery with vans
PD	probability that the customer within the "unmanned range" chooses delivery with UADV
PR	probability that the customer within the "unmanned range" chooses delivery with ADR

If a hybrid scenario is evaluated, the three probabilities can vary between 0 and 1 respecting the constraint:

$$PV + PD + PR = 1$$

Once the delivery method has been selected, customers will receive a notification relating to the delivery being taken over by the Local Hub agent. The resource-agent Van will then wait for a second message, which will change its status to 'waiting for delivery'. Delivery by van requires a small variation, namely that the customer is not at home at the time of delivery, in which case the delivery will be attempted again the following day. At this point, the customer can keep the package and return to the Idle state, or they have 30 days to return the parcel, waiting for the van to pick up the package to be returned (Figure 3).

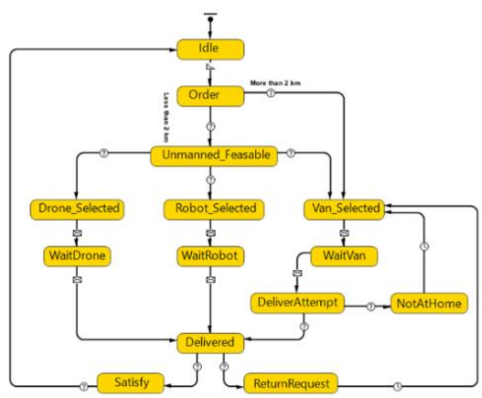

Figure 3 Agent "customer" behaviour state chart.

4.3. Modelling assumptions

The values of the parameters adopted to run the simulation are listed below:

- if scenario 1: PV=1, PD=0, PR=0.
- if scenario 2: PV=0, PD=1, PR=0.
- if scenario 3: PV=0, PD=0, PR=1.
- Unmanned range: 2 km.
- Clients: 3000.
- Daily demand : a simulation is performed for each demand level in the set $PV = [70,80,90,100,110,120]$

- Traffic: A simulation is performed for each traffic level (as defined in section 3.1).
- Number of UADVs in the system: A simulation is performed at different numbers of UADVs.
- Number of ADRs in the system: A simulation is performed at different numbers of ADRs.

As can be seen, some parameters have been fixed while others vary to provide the behaviour of the system as some of these parameters vary, assessing the different scenarios. The first simulations are carried out to select the optimal number of unmanned vehicles at different levels of demand. Subsequently, the 3 scenarios previously introduced are simulated and the data useful for calculating the KPIs already introduced are extracted. The outputs extracted from the simulation are:

1. Average tour length.
2. Total kilometres travelled.
3. Hours to complete deliveries.
4. Parcels to be delivered in outsourcing.
5. Parcels to be delivered in overtime.
6. Average hours to reach the customer.
7. Number of parcels delivered.

5. Results and Discussion

To start evaluating the KPIs of the 3 different delivery systems, it is foremost necessary to define the composition of the fleet of unmanned systems as the levels of demand vary. The size of the fleet will be such that it will minimize the unit cost, since this is the key performance indicator that connects demand and cost. To achieve this objective, the simulations were conducted by escalating the number of vehicles utilized for deliveries for each level of demand. Fleets composition are reported in Table 3.

Table 3 Unmanned fleet composition.

Parcels demand	Number of UADV	Number of ADR
70	3	16
80	3	17
90	3	18
100	3	19
110	3	20
120	3	20

5.1. TTC

The Time to Customer or TTC is an indicator that identifies the average duration of the package's transit from the local distribution centre to the customer. The value is an average of the times to deliver to all customers each day for the 10 simulated days. As the Figure 4 shows, the use of unmanned systems guarantees the best performance for the same demand. On average, the package will travel for a duration of 13.2 minutes in the case of UADV and 45.6 minutes in the case of ADR. The TTC was evaluated in 3 traffic conditions for delivery with traditional Vans. There is an increase in the TTC from 3.51 hours in the condition without traffic to 3.8 hours in medium traffic conditions up to 4.21 hours in high traffic conditions. Delivery with ADR, exhibit a lower level of performance compared to UADVs, as ADRs must navigate urban soil in accordance with its limitations, and operate at lower own speeds than UADVs. Finally, we have the performance of the van, in this case, customers at the end of the tour receive packages after a much longer time than what happens for the unmanned counterpart.

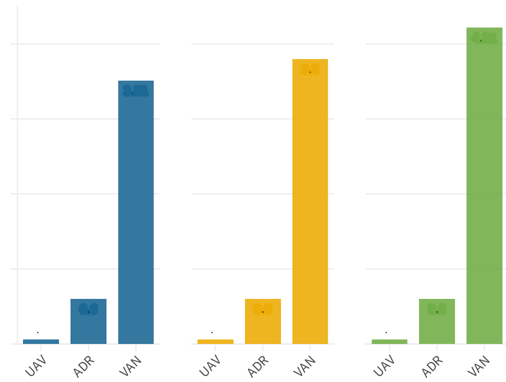

Figure 4 Time to customer comparison.

5.2. DR

The delivery rate (DR) is an indicator which provides the number of deliveries made in one hour. Furthermore, in this particular instance, we have opted to refer to the average values for each level of demand within the 10-day period during which delivery is implemented. It is also obtained that, in this case, the UADV has the best performance compared to the other two. From the Figure 5, it can be ascertained that the drone-based delivery system can deliver about 37 parcels per hour. The system based on ADR appears to have comparable performance to those of traditional vans, delivering about 16 parcels per hour. Even if they are negatively affected by the presence of traffic, vans can deliver between 14 and 12 parcels per hour in zero or average traffic conditions, but in high traffic conditions the DR drops to less than 10 parcels per hour.

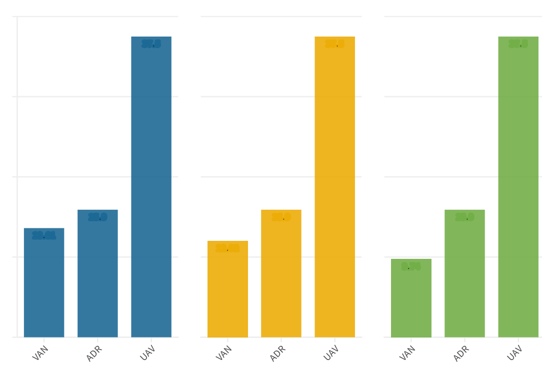

Figure 5 Delivery Rate to customer comparison.

5.3. UC

From the previous key performance indicators, we have obtained significant, but limited, indications. In this paragraph, we examine the unit costs using, a crucial KPI that joints data about the costs and the delivery performance of each system. Analysing the simulation data shown in the Figures 6, 7, 8, it can be seen that ADRs are the systems with the highest unit cost in zero or medium traffic conditions and for almost any level of demand. As far as UADV is concerned, for levels of demand equal to 70 and 80, they have unit costs slightly lower than those of traditional vans. For high levels of demand, delivery by van is better in zero and average traffic conditions (Figures 6 and 7). Regarding the high traffic conditions Figures 8, it can be observed that the introduction of overtime work (demand = 100) renders delivery with Vans less convenient compared to delivery with UADV. If the demand exceeds 120, you will need to have part of the demand delivered by external companies, making delivery by Van the least convenient of all.

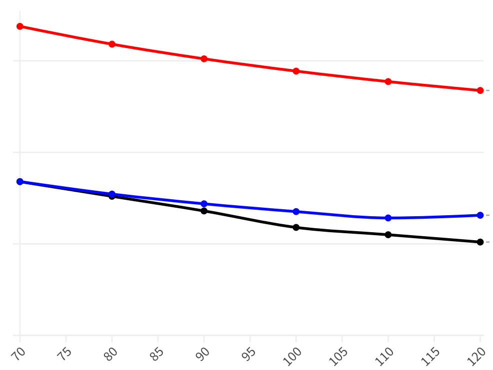

Figure 6 Unit Cost comparison with Van operating in no traffic condition.

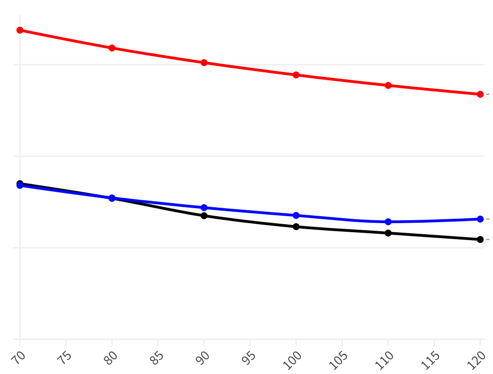

Figure 7 Unit Cost comparison with Van operating in medium traffic condition.

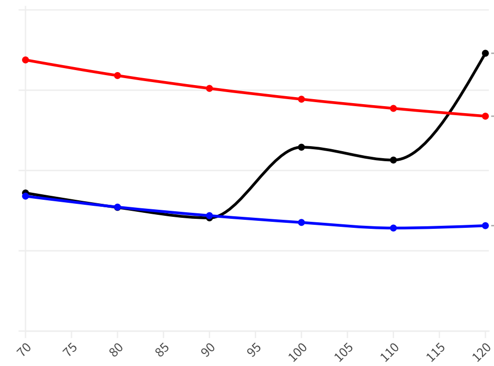

Figure 8 Unit Cost comparison with Van operating in high traffic condition.

5.4. Em

Finally, the last KPI to be analysed is that relating to CO2 equivalent emissions. Analysing delivery system based on conventional vans, the emissions pertaining to the utilization of fuel (Tank To Wheel: TTW) will be reported, along with the emissions pertaining to all activities that bring the fuel to the use stage (Well to tank). For the unmanned systems, emissions related to the production of electricity used to recharge the batteries of the delivery systems were evaluated. Based on our analysis, it has been determined that the utilization of UAVD for each level of demand appears to be the most efficient solution for reducing CO2 emissions, with values ranging from 63.24 kg to 110.15 kg of CO2e per year. However, emissions associated with the delivery with ADR are on average eight times greater due to their method of movement and lower effectiveness. As they are still based on fossil fuels, the emissions relating to delivery with internal combustion vehicles have much higher values approximately between 5500 and 7500 kg co2e per year in absence of traffic and between 6500 and 9000 kg co2e per year in high traffic condition.

6. Conclusions

The present study aims to model a last-mile delivery system using the Anylogic simulation tool. Using agent-based simulations and discrete events, it was possible to model not only the behaviour of the agents that usually populate an urban delivery system, but also the processes involved. Therefore, by simulating a delivery system based on UADV and ADR and comparing it with a delivery system based on traditional vans, it was possible to obtain key findings supporting the adoption of this type of technology.

The principal objective was to simulate the transport procedures of each vehicle, the interactions between agents and each other, and the setting in which they operate. Afterward, the parameters that would best characterize a delivery system were defined. These parameters were subsequently evaluated as inputs to observe the system's response as they varied. After obtaining the model and conducting a thorough testing of its correct functioning, the most indicative key performance indicators for a delivery system were formulated. The final steps involved the definition of the final results using defined key performance indicators.

Delivery robots and drones can help reduce carbon emissions compared to traditional delivery methods. The capability to operate on electric power makes these autonomous vehicles free of the need for burning fossil fuels and contributes to a healthier and more sustainable delivery ecosystem.

By evaluating the unit costs that combine information about delivery performance and total costs, we obtained that UADVs work better than the other two solutions for low demand levels; for high-demand levels, traditional delivery is still the better choice. The high total expenses make ADR a poor choice when it comes to unit expenses. When examining the issue of congestion, it is noteworthy that traditional vans exhibit the least efficient performance, particularly when it is necessary to utilize outsourcing for deliveries.

It is important to acknowledge that the widespread adoption of delivery robots and drones comes with certain challenges and considerations. These include policies and guidelines, security apprehensions, public acceptance, and the need for a sturdy network to enable the deployment of these innovations. It is imperative for policymakers, industry stakeholders, and researchers to collaborate to address these obstacles and establish an enabling environment that facilitates the sustainable integration of delivery robots and drones into our logistics systems.

For future research, it is suggested to think about hybrid systems, where the three systems could be used as one system using one of these technologies based on customer need and location. Moreover, it would be of considerable interest to contemplate the utilization of delivery to parcel lockers, small urban warehouses, or consolidation centres to mitigate the miles travelled and consequently mitigate costs and emissions. The authors also consider it essential to use simulation tools to verify how flight dynamics affect the parameters that influence the performance of UADVs. It might be helpful to use data about batteries and speeds from real tests to make new simulations.

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