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An Artificial Intelligence-based software module for the optimization of collaborative delivery in last-mile logistics

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Abstract: *This paper presents a route delivery planning and simulation module that forms a core part of the ICT Platform of the H2020 SENATOR project, which aims to enhance the sustainability of cities by developing a new urban logistic model. The module utilizes AI-based optimization algorithms to support the matching of supply and demand, identify the best fleet mix, and estimate the best delivery route based on real-time conditions. It also allows last-mile delivery planning using different transport modes, inter-modality, and driving restrictions, and simultaneously optimizes different performance indicators. The paper provides a detailed description of the AI-based optimization method and the architecture and components of the software module. Finally, the software module is validated in two scenarios (current operations and implementation of a Low Emission Zone) using real shipment data from a postal operator company in the living lab that the SENATOR project is implementing in Zaragoza.*

Keywords: *last-mile logistics, vehicle routing problem, optimization, dynamic planning, multi-modal, collaborative delivery.*

Conference Topic(s): *distributed intelligence last mile & city logistics; PI modelling and simulation; technologies for interconnected logistics (5G, 3D printing, Artificial Intelligence, IoT, machine learning, augmented reality, blockchain, cloud computing, digital twins, collaborative decision making)*

Physical Internet Roadmap *(Link): Select the most relevant area(s) for your paper:☐ PI Nodes, ☐ PI Networks, ☒ System of Logistics Networks, ☐ Access and Adoption, ☒ Governance.*

1 Introduction

The growth of last-mile logistics is a continuous trend, driven mainly by urbanization and changes in consumer behaviour. The surge in online retailing, e-groceries, and e-commerce has contributed to this phenomenon (European Commission, 2023). This trend has resulted in an increase in freight traffic in urban areas, which negatively impacts the sustainability and livability of our cities. The additional traffic generated by vehicles for deliveries leads to congestion and emissions, with CO2 accounting for 25% and PM and NOx accounting for 30-50%. Furthermore, heavy vehicles also reduce road safety (European Commission, 2020). On top of that, the COVID-19 pandemic has further accelerated the growth of online purchasing and logistic innovations(DHL, 2023). However, despite efforts to improve logistics sustainability, the challenges of the entire process are still subject to debate. Nevertheless, new technologies, processes and distribution strategies offer significant potential for enhancing the impact of last-mile deliveries in urban areas.

With these challenges in mind, the SENATOR project[1]aims to create a new urban logistic model for enhancing the sustainability of cities. For this purpose, the project will develop a smart network operator, as a control tower supported on an ICT Platform that will work as a support tool for decision-making, integration and planning of all logistics operations. In consequence, it will minimize the negative impacts that this distribution causes in the cities and will constitute an effective means of collaboration between agents (citizens, operators, carriers, and administrations).

The objective of this paper is to present one of the core parts of the mentioned ICT Platform. Concretely, the route delivery planning and simulation module whose aim is to support the matching of supply (vehicle, transport operators, etc.) with demand; to identify the best fleet mix (e.g. fuel, electric or zero-emission vehicles, cargo-bikes) to fulfil the customer demands while reducing pollution; and estimate the best delivery route according to real-time or historical traffic conditions (e.g. traffic congestion, etc.), to avoid the overlapping between different logistic/transport operators routes when possible to reduce traffic, and to overcome unexpected events that might arise, such as traffic disruptions or vehicle breakdowns thanks to the AI-based optimization algorithms. Furthermore, to show the capabilities of the software module, we validate it in a real scenario using shipment data from a postal operator company in the living lab that the SENATOR project is implementing in Zaragoza. The first scenario is based on the current operations of the postal operator, whereas the second one is based on the implementation of a Low Emission Zone in the city centre of Zaragoza.

The rest of the paper is structured as follows. Section 2 reviews other tools currently available that are similar to the one presented in this paper. Then, Section 3 is devoted to describing the AI-based software module for collaborative logistics. After that, the experimental setup and the results obtained by the system presented are detailed in Section 4. Finally, the main conclusions gathered from this paper a discussed in Section 5.

2 Related work

This section discusses various tools available for solving the Vehicle Routing Problem (VRP), that are similar to the one presented in this paper and provides a comparison among them.

- **JSprit[2]** is an open-source VRP engine written in Java and uses a generic Ruin & Recreate metaheuristic. It can solve different VRP variants, including Capacitated VRP, Multiple Depot VRP, VRP with Time Windows, VRP with Backhauls, VRP with Pickups and Deliveries, VRP with Heterogeneous Fleet, and Time-dependent VRP.
- **OR-Tools[3]** is an open-source software suite for optimization, tuned for tackling hard problems in vehicle routing, flows, integer and linear programming, and constraint programming. OR-Tools includes a specialized routing library to solve different types of node-routing problems, such as TSP, VRP, CVRP, VRPTW, VRP with Resource Constraints, and VRPPD.
- **VROOM[4]:** VROOM is open-source software written in C++ for solving vehicle routing problems. VROOM can solve several types of VRPs, including TSP, CVRP, VRPTW, MDHVRPTW, PDPTW, and a mix of these types.

[1] https://www.senatorproject.eu/
[2] https://github.com/graphhopper/jsprit/tree/master/docs
[3] https://github.com/google/or-tools
[4] https://github.com/VROOM-Project/vroom

- **VRP Service from ArcGIS**[5] is a commercial service developed by ESRI to address different routing problems. It can be accessed in different ways such as JavaScript APIs and SDKs in different programming languages.
- **Circuit**[6] is a commercial tool available on web service, Android and iOS platforms, that allows the optimization of up to 1000 stops considering stop time windows, first and last stop, and priority levels. Its main use cases are Driver Tracking, Local Delivery, Route Planning, Proof of Delivery, and Courier Management.
- **LOCUS**[7] is a commercial tool that allows the planning and optimization of routes and vehicle assignation for orders considering problems such as Travelling Salesman, Vehicle Routing and Knapsacking. LOCUS implements exact, heuristic, and hybrid algorithms. Its main use cases are Last-Mile Delivery Routing, Field Service Dispatch Planning, Dynamic Route Planning and Optimization, Territory-Based Route Planning, and Reverse/Returns Logistics.
- **OptaPlanner**[8] is an open-source tool developed in Java that implements several optimization problems, including VRP, Capacitated VRP, and VRP with Time Windows. It also allows integration with Google Maps and OpenStreetMap.
- **HERE**[9] is a commercial tool that provides a route planning API to solve the VRP, implementing the Capacitated VRP, VRP with Time Windows, Multi-Depot VRP, Open Vehicle Routing, Heterogeneous or Mixed Fleet VRP, and Pickup and Delivery VRP. It allows the calculation of routes using real-time and historical traffic information and the re-planning of routes in real time if new orders appear.
- **GraphHopper**[10] is an open-source software tool developed in Java that uses JSprit as the route optimization engine. It provides an API to solve a variety of vehicle routing problems, including the Traveling Salesman optimization problem, and all the VRP variants implemented in JSprit. Its main advantages are the possibility of designing vehicle types and defining time windows and service times for drivers.

However, none of the tools discussed above offer at the same time the functionalities of dynamic route optimisation, multi-modal fleet optimisation, inter-modal and/or transfer route optimisation, multi-objective optimisation and consideration of driving constraints.

3 Artificial Intelligence based software module for collaborative last-mile logistics

The software module for collaborative last-mile logistics is based on the well-known Rich Vehicle Routing Problem (Lahyani, Khemakhem, & Semet, 2015) which is a class of optimization problems that represent some or all aspects of a real-world application of vehicle routing including optimization criteria, constraints, and preferences. These problems deal with more realistic optimization functions, uncertainty, and dynamism, along with a wide variety of real-life constraints related to time and distance factors, and the use of heterogeneous fleets. Specifically, this software module internally implements a more realistic and complex model of the Rich Vehicle Routing Problem than those currently available in the literature as it can simultaneously incorporate the following aspects:

[5] https://desktop.arcgis.com/es/arcmap/latest/extensions/network-analyst/vehicle-routing-problem.htm
[6] https://getcircuit.com/
[7] https://locus.sh/
[8] https://www.optaplanner.org/
[9] https://developer.here.com/products/tour-planning
[10] https://github.com/graphhopper/graphhopper

- **Dynamism:** given that some elements of the delivery planning may change over time, the software module allows the re-adjustment of the planning (e.g. last-minute orders that may appear, a vehicle breaks down and it is necessary to assign orders to other routes)
- **Multi-modality:** the module allows last-mile delivery planning using different transport modes (e.g. walking, bikes, motorbikes, vans, etc.).
- **Inter-modality:** the software allows that one shipment can be transported by different transport modes along its route between the depot/pick-up location and the destination.
- **Multi-objective:** the module deals with the simultaneous optimization of different performance indicators (e.g. distance, time, emissions, etc.)
- **Driving restrictions:** the component allows the modelling of areas with access restrictions to specific vehicles (e.g. pedestrian zones, low emission zones, etc.)

In order to solve this highly complex Rich Vehicle Routing Optimization model, a specific sort of Artificial Intelligence techniques has been used. Concretely, we have used metaheuristics (Potvin & Gendreau Jean-Yves, 2019) because of their high efficiency and efficacy for this type of problem (Goel & Bansal, 2019). In a more specific way, the optimization algorithm designed is a hybrid metaheuristic(Gu, Cattaruzza, Ogier, & Semet, 2019) based on Large Neighbourhood Search (Pisinger & Ropke, 2019).

In the following subsections, we will describe the Artificial Intelligence-based resolution algorithm and the architecture of the software module.

3.1 Artificial Intelligence-based resolution algorithm

The Large Neighborhood Search (LNS) algorithm was employed in the resolution of the presented module, utilizing a metaheuristic in which the neighbourhood of a solution is implicitly defined through the use of destroying and repairing operators. The destroy operator eradicates a portion of the current solution, while the repair operator reconstructs the destroyed solution. The destroy method is usually implemented with some degree of randomness to modify different aspects of the current solution in order to explore the solution search space. LNS employs a larger neighbourhood exploration technique compared to other classical local search metaheuristic algorithms. The algorithm is a hybrid metaheuristic that combines various destruction and solution construction operators (ruin and recreate), as well as strategies to accept or reject solutions. Consequently, it is also integrated into numerous libraries related to the vehicle routing problem.

The optimization procedure pursued by the module is a stochastic approach based on the ruin and recreate (R&R) operator and can be summarized as follows:

1. Initiate the process with an initial feasible configuration.
2. Choose a ruin and recreate mode, i.e., a technique that will “destroy” the solution configuration, as well as the technique that will reconstruct the configuration.
3. Determine the number of nodes to be removed.
4. Ruin & Recreate. Generate a new solution using the heuristics selected in step 2.
5. Decide whether to accept the new solution based on a decision rule (Simulated Annealing, Threshold Accepting Criteria, etc.). If accepted, proceed to (2) using the new solution; otherwise, restart with (2) using the previous configuration.

3.2 Architecture and Components

The architecture of the proposed module is based on the distinct responsibilities and functionalities of its various components, each with its own distinct behaviours. It depicts the different components and their relationships. Certain components serve a specific purpose and have been designed to consolidate the optimization model. Within the optimization engine, several sub-modules are present:

- **Data Processing:** This module is responsible for processing all input data and translating it into the data structures utilized by the algorithm.
- **LLs Services:** This module is responsible for managing the different constraints and intricacies of the optimization model that must be associated with each use case.
- **Output Solution Processing:** This module is responsible for generating the output solution of the optimizer. Here, different key performance indicators (KPIs) that enable the evaluation of the solution are obtained.

The general module that encompasses the optimization engine is primarily responsible for 1) integration with the API-REST and all services; 2) the optimization engine that loads all data and creates the problem; 3) the integration with the JSprit framework; and 4) the processing the algorithm's solution to obtain the output API-REST.

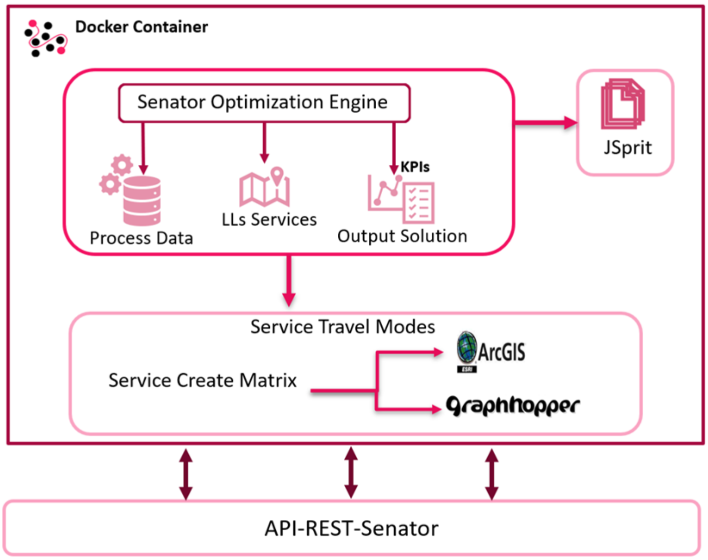


Figure 1 Architecture and components of the proposed module

Moreover, a JSprit module has been developed that bears the following responsibilities: 1) it contains the framework that implements the VRP problem, which has been modified to adapt to the dynamic delivery planning optimization model; 2) the primary modifications were made in the modelling of the constraints, operator strategies, and the computation of the fitness function.

A subsystem that is accountable for optimization has been developed based on specific tasks and requirements in the proposed model for each use case. Input data and the obtained solution will be stored in a database, which can be accessed through the API-REST. From the dynamic planning model for optimization, a last-mile route planning for different vehicles will be obtained, optimizing the use of available resources.

4 Experiments and Results

In order to validate the results of the system presented in this article, we have designed two scenarios: **Scenario 1)** which reflects the current operations of a real postal operator in the city of Zaragoza, and **Scenario 2)** which corresponds to the implementation of a Low Emission Zone in the centre of the city of Zaragoza. In addition, for each of the scenarios considered, three different fleet compositions have been simulated in terms of vehicle electrification ratio, with the aim of showing the capabilities of the tool for measuring the impact that different levels of fleet electrification would have on the two scenarios defined.

Below we provide more details about the experimental framework designed and the results obtained for the two scenarios designed and the alternative fleet compositions

4.1 Experimental framework

This section aims to define the two scenarios considered for the validation of the route optimisation software module, as well as the different fleet compositions considered in the experimentation.

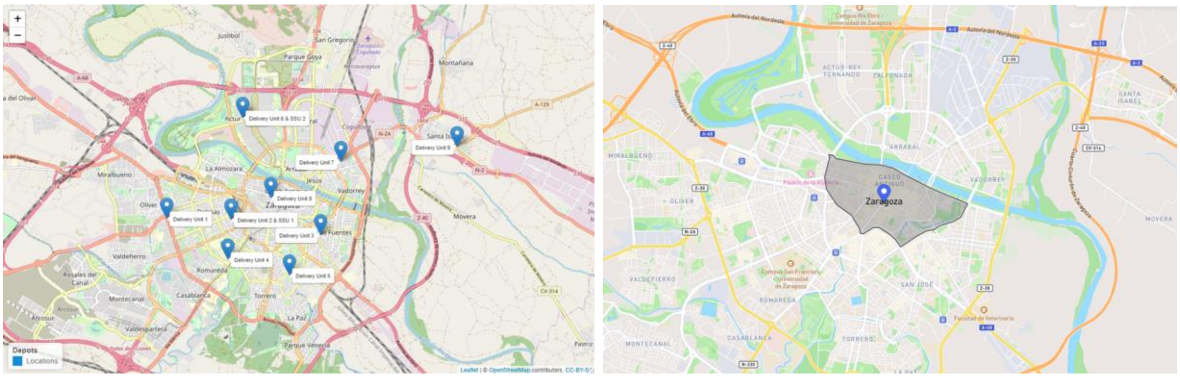
4.1.1 Scenario 1: Baseline Scenario

Scenario 1 reflects the current situation of postal operations in the urban area of Zaragoza, where the following infrastructure is in place: **A) Nine Delivery Units (DUs)** distributed throughout the city and dedicated to the delivery of postal items and small parcels. Most of the routes are done by postmen/postwomen on foot; **B) Two Special Service Units (SSU)** that are located in the northern and southern areas of the city, respectively. They specialise in the delivery of larger parcels and therefore all routes are done with a motorised vehicle.

Figure 2 A) shows the distribution of the DUs and SSUs in the city of Zaragoza. As for the operation of the routes, the postal operator works in two shifts, one in the morning and one in the afternoon. The morning shift runs from 7:00 am to 3:00 pm, while the afternoon shift runs from 3:00 pm to 10:00 pm. Since postmen need time at the beginning of the shift to sort and prepare the items to be delivered and at the end of the shift to dispose of undelivered items, the time slots in which postmen run their delivery routes are from 8:00 am to 2:00 pm in the morning shift, and from 4:00 pm to 9:00 pm in the afternoon shift. As for the demand data, for the purpose of analysis, we have chosen the data on deliveries made by the postal operator on 13 and 14 September 2022, which we show in Table 1 as distributed by day and by shift.

4.1.2 Scenario 2: Deployment of a Low-Emission Zone

The second scenario we have defined for this analysis considers the deployment of a Low Emission Zone in the historic centre of the city of Zaragoza, whose delimitation is shown in Figure 2 B). The deployment of this Low Emission Zone implies that polluting vehicles cannot enter the area between 7 am and 11 pm. This would affect postal operations in the area since combustion vehicles would not be able to access the zone for delivery. Only postmen/postwomen on foot or electric vehicles would be able to deliver items to the designated area. The percentage of the orders that would be affected by the Low Emission Zone is shown in Table 1. As can be seen, the percentage of orders falling within the Low Emission Zone ranges between 9% and 15% depending on the shift and the day.



A) B)

Figure 2 – A) Image of the area of study for the Zaragoza Scenario 1 and location of the DUs and SSUs, and B) Delimitation of the area considered for the deployment of the Low Emission Zone in Zaragoza

Day	Working Shift	Number of Shipments	% of shipments in the Low Emission Zone
Sept 13, 22	Morning	11723	15%
Sept 13, 22	Afternoon	3794	9%
Sept 14, 22	Morning	11429	15%
Sept 14, 22	Afternoon	4296	13%

Table 1 Number of shipments per day and shift, and percentage of shipments in the Low-Emission Zone in each zone

4.1.3 Alternative fleet compositions

As mentioned before, have defined three different fleet compositions in terms of fleet electrification in order to understand what impact it may have in environmental and operational terms. The three fleet compositions considered are as follows:

- **Current fleet composition:** in this alternative, the fleet has the same composition as the current postal operator fleet shown in Table 2.
- **Electrification 50%:** in this case, a fleet electrification of around 50% is considered, following the same composition in terms of vehicle typology.
- **Electrification 100%:** in this last alternative fleet composition, 100% electrification is considered, i.e., all vehicles in the fleet are electric. Similar to the previous case, the typology of the vehicles is maintained with respect to the current composition.

Vehicle Type	Technology	Current composition	Electrification 50%	Electrification 100%
Large Van	Combustion	9	9	-
Large Van	Electric	-	-	9
Motorcycle	Electric	12	27	27
Small Van	Combustion	37	15	-
Small Van	Electric	2	24	39

Table 2 - Number of vehicles per type and technology for each of the fleet composition alternatives

4.2 Result analysis

In this section, we will analyse the results obtained by the software module presented in the two scenarios defined and for each of the fleet compositions. For this analysis of the results, we will consider the indicators shown in Table 3, which are provided by the route optimisation system presented in this article. In the two following subsections, we discuss the results obtained in each of the scenarios. More details about the calculation of the indicators can be found in (Vincenzo et al., 2022).

Impact area	Criteria	Indicator	Data/unit
Environment & Society	Air quality	CO concentration	g/day
		SOx concentration	g/day
		NOx concentration	g/day
		NH3 concentration	g/day
		PM10 concentration	g/day
	GHG emissions	CO2	g/day
		CH4	g/day
		N2O	g/day
	Social costs	Social costs of air quality and GHG emissions	€/day
Transport & mobility	Accessibility	Number of shipments	n./day
		Number of routes	n./day
		Total km covered (including walking)	km/day
		Total km covered by green modes (including walking)	km/day
		Total veh-km covered by freight vehicles	Veh-km/day
		Total veh-km covered by green freight vehicles	Veh-km/day
	UFT vehicles	Vehicle utilisation factor	%/day
	Operative costs	Fixed costs	€/day
		Running costs	€/day
		Capital costs	€/day

Table 3 Indicators considered for the analysis of results

4.2.1 Results for Scenario 1

Table 4 shows the results for scenario 1 with the different fleet compositions. As can be seen, with the current fleet having a high percentage of conventional vehicles, the environmental impact is high, reaching a social cost of more than €17,75 per day. However, by increasing the electrification of the fleet, emissions are reduced by around 85%, as is the social cost. This more than 50% increase is due to the fact that the postal operator fleet is oversized to cope with peak demand. Therefore, with 50% of the current fleet electrified, emissions would be reduced by 85% in periods of intermediate demand. With 100% electrification of the fleet, as expected, the environmental impact is reduced by 100%.

Furthermore, as we can see and as expected, the impact in terms of operations is nil as in all cases the same service levels are maintained. However, in terms of operational costs, the electrification of the fleet implies a slight increase in fixed costs and mainly in capital costs (60%), due to the higher price of electric vehicles. On the positive side, however, running costs would be reduced by 40%.

4.2.2 Results for Scenario 2

The results of scenario 2 for the implementation of a Low Emission Zone are shown in the table below. If we look at the environmental impact of the different levels of electrification, we see that the results are very similar to those of the previous scenario, as is to be expected. Where we do see some differences is in the number of shipments delivered, which increases by around 1% with higher electrification of the fleet, which is the same as the decrease in the number of shipments delivered when compared to scenario 0 for the current postal fleet. This 1% increase is due to the fact that with increased electrification of the fleet, more vehicles can access the Low Emission Zone and therefore deliver more parcels.

Indicator	Scenario 1 Fleet Compositions			Scenario 2 Fleet Compositions		
	Current Comp.	50% Electric Vehicles	100% Electric Vehicles	Current Comp.	50% Electric Vehicles	100% Electric Vehicles
CO concentration	152,58	11,01	0,00	144,58	11,01	0,00
SOx concentration	1,00	0,14	0,00	0,97	0,14	0,00
NOx concentration	589,18	108,37	0,00	566,32	108,36	0,00
NH3 concentration	2,90	0,40	0,00	2,82	0,40	0,00
PM10 concentration	27,83	4,90	0,00	26,52	4,90	0,00
CO2	197.936,30	27.555,43	0,00	190.998,58	27.553,29	0,00
CH4	14,68	1,21	0,00	13,80	1,21	0,00
N2O	11,64	1,97	0,00	11,34	1,97	0,00
Social costs of air quality and GHG emissions	17,75	2,48	0,00	17,13	2,48	0,00
Number of shipments	8.873,60	1.240,12	0,00	14.930,00	15.058,50	15.107,50
Number of routes	15.106,00	15.083,50	15.107,50	208,00	206,00	207,00
Total km covered (including walking)	208,00	206,00	207,00	2.695,79	2.703,98	2.722,50
Total km covered by green modes (including walking)	2.722,30	2.702,36	2.722,50	1.418,84	2.519,88	2.722,50
Total veh-km covered by freight vehicles	1.390,51	2.518,24	2.722,50	1.657,42	1.665,62	1.684,14
Total veh-km covered by green freight vehicles	1.683,94	1.664,00	1.684,14	380,47	1.481,52	1.684,14
Vehicle utilisation factor	0,33	0,33	0,33	0,32	0,33	0,33
Fixed costs	24.612,49	24.683,48	25.008,18	24.328,19	24.659,85	25.008,18
Running costs	187,99	112,47	106,57	184,26	112,59	106,57
Capital costs	1.154.800	1.507.800	1.842.800	1.198.800	1.507.800	1.842.800

Table 4 – Results for Scenario 1 and Scenario 2

5 Conclusions

In this paper, we have presented a route delivery planning and simulation module that forms a core part of the ICT Platform of the H2020 SENATOR project. The module utilized AI-based optimization algorithms to support the matching of supply and demand, identify the best fleet mix, and estimate the best delivery route based on real-time and historical conditions. It also allows last-mile delivery planning using different transport modes, inter-modality, and driving restrictions, and simultaneously optimizes different performance indicators. We have also provided a detailed description of the AI-based optimization method and the architecture and components of the software module. Furthermore, the software module has been validated in two scenarios using real shipment data from a postal operator company in the living lab that the SENATOR project is implementing in Zaragoza.

The main conclusions from the two scenarios analysed and simulated with the presented tool are the following. In scenario 1, it is found that increasing the electrification of the fleet results in a significant reduction in emissions and social costs, with 100% electrification reducing the environmental impact by 100%. However, there is a slight increase in fixed and capital costs due to the higher price of electric vehicles. In Scenario 2, the results show that the environmental impact reduction of fleet electrification is similar to Scenario 1. However, there is an increase in the number of shipments delivered with higher electrification of the fleet due to higher access to the Low Emission Zone.

Overall, the presented tool has shown that increasing the electrification of the fleet is an effective way to reduce the environmental impact of postal operations, with the added benefit of increased access to Low Emission Zones. The drawbacks found by the tool are that there may be some additional costs associated with electrification.

In short, these results have validated that the presented tool is novel and that it allows the optimisation and simulation of last-mile logistics considering different elements of high relevance nowadays such as fleet electrification or the implementation of low-emission zones. More details about the results of the algorithm in other scenarios and using real data from the city of Dublin can be found in (Vincenzo et al., 2022)

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