D3.3: AI-Driven Models and Services

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101069782

URBANE

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2030
Sustainable and smart mobility for all

Project & Document Information

Grant Agreement No	101069782	**Acronym**	URBANE
Project Full Title	UPSCALING INNOVATIVE GREEN URBAN LOGISTICS SOLUTIONS THROUGH MULTI-ACTOR COLLABORATION AND PI-INSPIRED LAST MILE DELIVERIES		
Call	HORIZON-CL5-2021-D6-01		
Topic	HORIZON-CL5-2021-D6-01-08	**Type of action**	IA
Coordinator	INLECOM INNOVATION		
Start Date	01/09/2022	**Duration**	42 months
Deliverable	D3.3	**Work Package**	WP 3
Document Type	OTHER	**Dissemination Level**	PU
Lead beneficiary	SKEMA		
Responsible author	Ade FAJEMISIN		
Contractual due date	31/08/2024	**Actual submission date**	31/08/2024

Disclaimer and Acknowledgements

Co-funded by the European Union

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Version History				
Version	**Date**	%	**Changes**	**Author**
0.1	25/07/2023	5%	Wrote the ToC	Ade Fajemisin (SKEMA)
0.2	08/03/2024	80%	Wrote and assembled the sections	Ade Fajemisin (SKEMA) Kostas Zavitsas (VLTN)
0.3	12/08/2024	90%	Wrote and assembled the sections	Ade Fajemisin (SKEMA) David Rey (SKEMA) Xavier Brusset (SKEMA) Kostas Zavitsas (VLTN)
1.0	26/08/2024	100%	Addressed comments in peer review	Ade Fajemisin (SKEMA)

Quality Control (includes peer & quality reviewing)			
Date	**Version**	**Name (Organisation)**	**Role & Scope**
30/07/2023	0.10	Efstathios Zavvos (VLTN)	QM ToC Approval
14/08/2024	0.31	Maria Kampa (INLE)	Peer review
16/08/2024	0.32	Yasanur Kayikci (VLTN)	Quality Check
31/08/2024	1.00	Ioanna Fergadiotou (INLE)	Coordinator Approval

Executive summary

In urban logistics, collaboration among service providers offers a promising solution to enhance efficiency and reduce emissions. This document outlines five key innovative AI-driven models and services developed in the scope of URBANE: Demand Prediction, Collaborative Delivery, Dynamic Parcel Reshuffling, Automatic Delivery Vehicle (ADV) Routing Simulator, and Cost Benefit Analysis Tool aimed at greening last mile logistics.

Demand Prediction: Leveraging predictive modeling techniques, this model forecasts future delivery demands, aiding in fleet-sizing decisions and minimizing vehicle standby time.

Collaborative Delivery: By optimizing delivery routes and sharing workload among providers, this model reduces distance traveled and CO_2 emissions. Initial simulations in the Bologna Living Lab indicate a 10.65% reduction in both distance and emissions.

Dynamic Parcel Reshuffling: Urban delivery faces uncertainty due to congestion, parking, and recipient availability. This model dynamically redesigns delivery routes based on real-time conditions, utilizing regression, clustering, and vehicle routing techniques.

ADV Routing Simulation: This model is used in conjunction with the agent-based model developed by NORCE to simulate consumer acceptance of ADVs. It simulates the interaction of customers with ADVs and calculates delivery times, parcel delivery success rates, emissions, and customer queue lengths.

Cost Benefit Analysis: The CBA tool assesses the costs and performance of last mile and middle mile urban deliveries. It evaluates infrastructure investments and operational models, focusing on Bologna's green delivery initiatives. The tool calculates daily costs, projects long-term financial impacts, and estimates break-even points for delivery operations.

Discussion and Recommendations: While further evaluations are ongoing, strategic recommendations emphasize the importance of data collection and sharing, stakeholder incentivization, and model reusability for future living labs.

Conclusion: These models offer tangible benefits in reducing emissions, optimizing delivery operations, and enhancing urban livability. Continued refinement and implementation hold the potential to transform last mile logistics into a greener and more sustainable system.

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Glossary of Terms and Acronyms

TABLE 1 GLOSSARY OF ACRONYMS AND TERMS.

Acronym / Term	Description
ADV	Automatic Delivery Vehicle
CBA	Cost Benefit Analysis
CDM	Collaborative delivery model
DT	Digital Twin
DPRM	Dynamic Parcel Reshuffling Model
EDV	Electric Delivery Vehicle
LEZ	Low Emission Zone
LL	Living Lab
LM	Last Miler
LTZ	Low Traffic Zone
NPV	Net Present Value
PI	Physical Internet
UDR	Unsuccessful-and-Small-Deliveries-Scheduling/Rescheduling

1. Introduction

1.1 Deliverable Overview

This document describes the models developed in Task 3.5 (AI-driven models and services) under Work Package 3. This task develops AI-driven models and services that were employed in the Wave 1 Living Labs (LLs) context and integrated into the project's Digital Twin (DT) application.

1.2 Report Structure

This report is structured as follows.

A brief overview of the aims of the models developed in Section 2. The demand prediction model is described in Section 3, while the collaborative delivery model is described in Section 4. The dynamic parcel reshuffling model and the ADV routing simulator model are described in Sections 5 and 6 respectively. The cost-benefit analysis tool is described in Section 7, and the results of the case studies carried out are presented in Section 8. Finally, discussions and conclusions are given in Sections 9 and 10 respectively.

1.2 URBANE Outputs Mapping to GA Commitments

TABLE 2 DELIVERABLE ADHERENCE TO GRANT AGREEMENT DELIVERABLE AND WORK DESCRIPTION.

URBANE GA Item	URBANE GA Item Description	Document Chapter(s)	Justification
DELIVERABLE			
D3.3 AI-driven models and services	*AI-driven models that will be employed in the LLs. These models are designed to foster sustainable urban logistics in the LLs.*	*All Sections.*	*The goal of the 5 (five) models described in the Sections 3, 4, 5, 6 &7 is to minimize the total amount of emissions in last mile deliveries by estimating the number of vehicles required to fulfil deliveries, optimally assigning parcels to last milers and micro-hubs, dynamically reallocate parcels to delivery vehicles to avoid late deliveries, support the evaluation of the acceptance of automated delivery vehicles among customers, and assess the costs and long-term financial impacts of the designed interventions.*
TASK			

ST3.5.1 Demand prediction modelling via statistical learning	*Demand prediction modelling via statistical learning, to obtain predictions and probability distribution of stochastic parameters for users (customers) and delivery service providers.*	*Section 3*	*To minimize the number of delivery vehicles used (and consequently the total amount of emissions), a predictive model was developed using historical data to forecast the number of vehicles that will be required for a given delivery round. This model will be used in conjunction with the UDR model previously developed by INLECOM.*
ST3.5.2 Request-to-courier assignment via combinatorial auctions	*Development of a platform that identifies the best assignment of deliveries to couriers in order to reduce emissions.* *Development of a model that helps to evaluate consumer acceptance of automated delivery vehicles.*	*Sections 4 to 7*	*To reduce the total number of delivery vehicles operating in an area, these models determine the optimal assignment of parcels to last milers and micro-hubs and promote collaboration among delivery service providers. The result of this is a reduction in distance travelled and total emissions.*
ST3.5.3 Online optimization for same-day delivery using reinforcement learning	*Development of a model that identifies the best assignment of deliveries to couriers in an online manner in order to reduce emissions.*	*Sections 4 & 5*	*To avoid late deliveries based on congestion, parking and recipient availability, these models are implemented to dynamically redesign delivery routes.*

1.3 Adjustments of the WP sub-tasks activities

During the course of the project, discussions among stakeholders revealed that some of the initial sub-tasks of WP 3.5 could be adjusted to deliver targeted outcomes suited to different LLs. The availability of data also influenced model design and, accordingly, the following deviations from the initial plan were implemented.

Adjustment of ST 3.5.2: discussions with the project partners revealed that developing an assignment model based on combinatorial auctions was not the most effective approach to incentivize greener last mile deliveries. Accordingly, we developed a hierarchical game model that better reflects the existing dynamics among first- and last mile service providers, as well as city-level authorities. This adjusted courier-to-request assignment model is based on bilevel optimization, a flexible modelling approach that allows us to optimize multiple objectives: the objectives of delivery service providers, i.e. cost minimization and on-time deliveries, while also obtaining a broader green urban environment. This aims to act as an incentive for delivery service providers to join the platform, thus contributing to reducing emissions while ensuring service quality.

Adjustment of ST 3.5.3: discussions with the project partners revealed that online, i.e. (near) real-time reoptimization of delivery service routes and schedules was not the priority of the stakeholders and not in line with the developed Use Cases. Accordingly, the focus of this sub-task was adjusted to address two goals: i) developing a within-day dynamic parcel shuffling approach to provide more flexible service by allowing delivery vehicles to exchange parcels at optimized meeting points; and ii) developing a routing model for autonomous delivery vehicles (ADV) operations. Both of these adjustments were implemented in coordination with project partners and targeted LLs.

Although the cost-benefit analysis (CBA) tool was not originally part of the project proposal, its integration became essential as the project evolved. Stakeholders played a pivotal role in bridging the gap between the model outcomes and their broader economic implications, recognizing the necessity of evaluating the financial viability and impact of the proposed solutions. As discussions progressed, it became clear that the CBA would provide valuable insights, helping to quantify the economic trade-offs and benefits associated with different strategies. Consequently, the CBA tool was developed concurrently, even though it was not explicitly outlined in the initial proposal.

2 Background on AI-driven Models and Services

Service provider cooperation and collaboration is a prominent potential alternative to improve urban logistics (Savelsbergh & Van Woensel, 2016). Last mile logistics in city centres can be consolidated through collaboration models (Ranieri et al., 2018), and delivery fleets can be optimized using a combination of predictive models and optimization models. These models facilitate service provider collaboration as a means of reducing traffic and emissions in low-emission zones (LEZs) and low-traffic zones (LTZs) of a city. AI algorithms can optimize the logistic network in ways such as dynamic parcel reshuffling, optimal assignments to consolidation hubs, collaborative deliveries, fleet-sizing, and online optimization of deliveries for efficient transportation throughout the day.

Demand prediction modelling is a vital component in optimizing supply chains, impacting areas such as inventory management and delivery efficiency. Recent advances emphasize machine learning models like neural networks and ensemble methods, which outperform traditional statistical models by capturing complex, nonlinear patterns in demand data. LSTMs and attention mechanisms have proven particularly effective in time-series forecasting, managing fluctuating demand in sectors like retail and e-commerce (Borovykh et al., 2018). Integrating external factors, such as economic indicators and social media trends, via big data analytics has further enhanced prediction accuracy, enabling more proactive inventory management (Taylor & Letham, 2020).

Collaborative delivery has gained traction as companies seek to reduce costs and environmental impact through shared logistics resources. Recent studies highlight the role of digital platforms and IoT in enabling real-time data sharing among stakeholders, which enhances route optimization and reduces operational inefficiencies (Boukherroub et al., 2019). Blockchain technology is also being explored to improve transparency and trust in collaborative logistics networks, offering secure, traceable transactions (Saberi et al., 2019). Additionally, crowdsourced delivery models, coordinated through mobile apps, have become a popular solution for handling last-mile deliveries, though they pose challenges related to regulatory compliance and service consistency (Punel & Stathopoulos, 2020).

Dynamic parcel reshuffling, which adjusts delivery routes in real-time, is increasingly adopted to improve delivery flexibility and efficiency. Recent advancements in optimization algorithms, such as deep reinforcement learning, have significantly improved the ability to reconfigure routes dynamically based on real-time data inputs (Nazari et al., 2018). The integration of IoT and big data has enabled logistics companies to monitor traffic, weather, and package status in real-time, facilitating more informed and responsive decision-making (Tang et al., 2021). Moreover, customer-centric delivery options, allowing for real-time changes to delivery preferences, are becoming more prevalent, contributing to higher customer satisfaction (Savelsbergh & Van Woensel, 2016).

The developed algorithms will be coded into programs such that they can be implemented in the LLs for operational purposes, to help operators in their decision-making activities.

3 Demand Prediction Modelling

This section is devoted to explaining the need for demand prediction modelling, as well as the methodology used. We then explain how the models developed cover the expected outcome from ST 3.5.1 in the DoA.

3.1 Motivation for Demand Prediction

This approach allows us to estimate the number of delivery vehicles (conventional, electric, hybrid, and others) required to establish logistics services in a network for given future period. The model developed here is used in conjunction with the Unsuccessful-and-Small-Deliveries-Scheduling/Rescheduling (UDR) model developed in LEAD project[1] (GA 861598) from INLECOM. The output of these models was used to estimate the number of vehicles required to facilitate deliveries for specific sets of delivery orders.

3.2 Modelling Approach

3.2.1 What is Predictive Modelling?

Predictive modelling is an approach where data from events that have already occurred are analysed to deduce patterns in these events. Once these patterns have been identified, they can be used to forecast future events (Kuhn & Johnson, 2013).

3.2.2 Overview of Predictive Models

The predictive models we have employed are time-series models (Olson & Araz, 2023) as well as clustering models. The time series models are applicable because delivery data is often recorded over equally spaced periods of time. For example, it is common to see delivery data recorded daily, weekly, monthly, or yearly. The time-series models have been developed to exploit this structure and can find trends and seasonal effects in the data. With the availability of more data, it is expected that these models can be updated, and their results can be enhanced. Additionally, some specific models such as deep neural networks (Tedjopurnomo et al., 2022), which benefit from a large amount of data were evaluated for use.

3.2.3 Methodology- Application to the Fleet-Sizing Problem

Deliveries are made to a number of locations using several types of delivery vehicles (van, bike, car, etc). In order to forecast the number of vehicles to be used, we first have to determine the number of parcels to be delivered. Trying to forecast which specific address gets will get a parcel delivered is inefficient and likely to result in a very poor model. We therefore forecast parcels going to an area comprising several addresses. We base these predictions based on historical data, i.e. the location of deliveries that have occurred in the past, as well as the types of vehicles used to facilitate these deliveries.

We first split the addresses into groups using k-means clustering. We then forecast the number of deliveries going to each cluster, and the types of vehicles that will be used. This approach results in a much more accurate model. Once the number of clusters has been chosen (by the user) and the addresses have been clustered, we can forecast the number of deliveries going to each cluster on a given

[1] https://www.leadproject.eu/

day. The forecast will cover the next day or a specified number of future days, depending on the user requirements. Afterwards, the total number and type of vehicles required can then be determined given the forecasted number of parcels to be delivered. This forecast will enable more informed decision-making regarding vehicle allocation and should help us keep fewer vehicles on standby.

3.2.4 Data Specification

The input data required to run the model, and the output data describing the results are given in Tables 3 and 4 respectively.

TABLE 3 INPUT DATA FOR THE DEMAND PREDICTION MODEL.

Input Data	File type	Description
deliveries_data_as_is_UC3_initial	.xlsx	A dataset containing a set of historical deliveries. Information includes date of delivery, delivery times, delivery location, total number of parcels delivered, and the type of vehicle used for delivery.
input_params	.xslx	A table describing the number of clusters to use in the model and the number of days to forecast.

TABLE 4 OUTPUT DATA FOR THE DEMAND PREDICTION MODEL.

Output Data	File type	Description
deliveries_data_as_is_UC3_forecast	.xlsx	The forecasted number of deliveries going to each area for each vehicle type.

4 Collaborative Delivery Model

4.1 Motivation for the Collaborative Delivery Approach

Delivery service providers often service the same areas of the city at the same time. It is envisaged that by fostering collaboration between these service providers, we can reduce the overall number of delivery vehicles in an area. We can also reduce the overall distance travelled in the LEZs and LTZ. As emissions are a function of fuel consumption, which is itself a function of distance travelled, minimizing the total distance travelled over a network results in minimizing the total amount of emissions. This also results in the reduction of any associated negative effects like noise and congestion and drive cities towards the Physical Internet approach adoption. Figure 1 below shows an example of a scenario where two last mile operators (LMs) must deliver a set of parcels across a network. On the left-hand side of the figure, the LMs are uncoordinated and thusly travel over the entire network. On the right-hand side, the LMs have been assigned parcels to deliver such that there is much less overlap in the coverage areas, less distance covered by each individual LM, and fewer emissions and vehicles in the LEZ/LTZs.

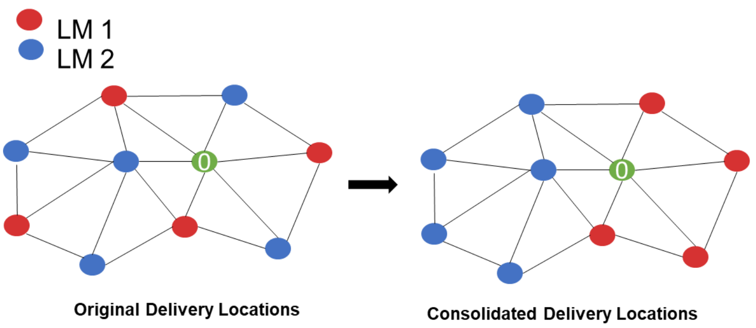

FIGURE 1 EXPECTED RESULT OF A COLLABORATIVE DELIVERY APPROACH

4.2 Modelling Approach

4.2.1 What is Bilevel Optimization?

Bilevel optimization (Sinha et al., 2018)is a modelling approach that allows the optimization problems of several individuals to be considered at the same time. The goals of these different individuals may be somewhat conflicting, and so some of the decision makers must anticipate the decisions of other decision makers and act accordingly. These individuals can be grouped into **leaders** and **followers**. The leader must make a decision while anticipating the response of the followers to the leader's chosen strategy.

4.2.2 Methodology- Application to the Green Collaborative Delivery Problem

In our model, the **leader** represents a platform controlled by a city or government authority with the primary goal of minimizing emissions and reducing the number of LM delivery vehicles operating within the city's LEZ or LTZ. The model involves two types of **followers**:

1. **First-Mile Followers**: These are responsible for transporting packages from their source locations to the micro-hubs. Their objective is to minimize the cost of routing required to deliver packages to these micro-hubs.
2. **Last-Mile Followers**: These pick up packages from the micro-hubs and deliver them to end customers within specific time windows. Their priority is to ensure on-time delivery, potentially using as many vehicles as necessary to avoid delays.

The conflict arises because while the LM followers might want to maximize vehicle usage to ensure timely deliveries, the leader (city authority) aims to minimize the number of vehicles in the LTZ to reduce emissions and congestion. This situation is well-suited for bilevel optimization, where the leader's decision to assign packages and routes influences the followers' routing choices.

In this model, the leader first assigns packages to micro-hubs, and then from these micro-hubs to LM operators in a way that minimizes the total emissions and the number of vehicles. After the leader's assignment, the followers optimize their delivery routes accordingly. The assignments are done in such a way as to anticipate the followers' response, so that the leader can find the optimal assignments based on what it expects the followers to do. The outcome not only reduces emissions but also decreases noise, traffic congestion, and the use of urban space.

4.2.3 Data-Driven Collaborative Delivery Model

The bilevel model is computationally demanding and requires hours to solve for a large number of deliveries. We therefore developed a data-driven variant of the model, which can be solved in much faster time. We first trained a predictive model over the complete delivery network of the city, with the goal of learning the emissions associated with deliveries to different destinations in the network. Once the model has been trained, it was incorporated into an optimization model that optimally assigns parcels to micro-hubs and to last milers with the goal of minimizing the total emissions associated with these assignments.

4.2.4 Data Specification

The input data required to run the collaborative delivery model, and the output data describing the results are given in Tables 5 and 6 respectively.

TABLE 5 INPUT DATA FOR THE COLLABORATIVE DELIVERY MODEL.

Input Data	File type	Description
city_network_training_config	.xlsx	A list of address locations parcels to be delivered and the locations they are to be delivered to
electricity_generation_breakdwn	.xslx	A table with parameters describing the different sources used to generate electricity, the emissions factor associated with each source.

locker_capacities	.xlsx	A table giving the capacity for each micro-hub.
last_milers	.xlsx	A table giving the location and number of vehicles for each last miler.
problem_instance	.xlsx	A table detailing the earliest and latest arrival times at each destination node, the amount of time the robot waits at a node, and the number of customers arriving per minute at that node.
battery_capacity	.xlsx	The battery capacity of the electric delivery vehicles to be used for deliveries.

TABLE 6 OUTPUT DATA FOR THE COLLABORATIVE DELIVERY MODEL.

Output Data	File type	Description
Distance and Emissions	.xlsx	The total distance (in km) and total emissions (in gCO2eq) for each last miler.
Assignments to Lockers	.xslx	The micro-hub to which each parcel is assigned.
Package Arrival Times	.xlsx	The time at which each parcel arrives at its final destination.

5 Dynamic Parcel Reshuffling Model

5.1 Motivation for Dynamic Parcel Reshuffling

The congested urban environment and the multiple different functionalities it accommodates, impose significant uncertainty in last mile delivery operations. Uncertainty is observed in travel times due to road congestion, parking availability in proximity to the delivery location, information accuracy associated with package drop off location, as well as when applicable uncertainty about the presence of the recipient at the time and location of the drop-off. Last mile operators frequently assume a unilateral travel speed and drop-off duration in their planning process to relax this complexity. Depending on the conditions encountered during the delivery round, last mile operators frequently need to dynamically redesign urban delivery rounds, to alleviate delivery delays. The aim of the Dynamic Parcel Reshuffling Model (DPRM) is to operate in a live setting, automate and optimise this process or act as a smart decision support tool for last mile operators.

5.2 Modelling Approach

5.2.1 What are Regression, Clustering and Vehicle Routing?

Three main techniques are used in this model, namely regression, clustering, and vehicle routing. Regression is a statistical technique that enables us to find the relationship between an 'outcome variable', and the 'explanatory' or input variables (Huang, 2022). Clustering is a technique that allows us to group similar objects together (Ikotun et al., 2023), while vehicle routing problem is an approach that allows us to find the shortest path a vehicle can take through a set of locations (Braekers et al., 2016).

5.2.2 System Overview

As illustrated in figure 2 below, the Dynamic Parcel Reshuffling Model (DPRM) is composed of three core sub-models: the first sub-model identifies avenues in which the workload can be shared between vehicles, the second reshuffles the parcels among the helper vehicles, and the third sub-model identifies a meeting point where the parcels can be exchanged and redesigns the new driver instructions.

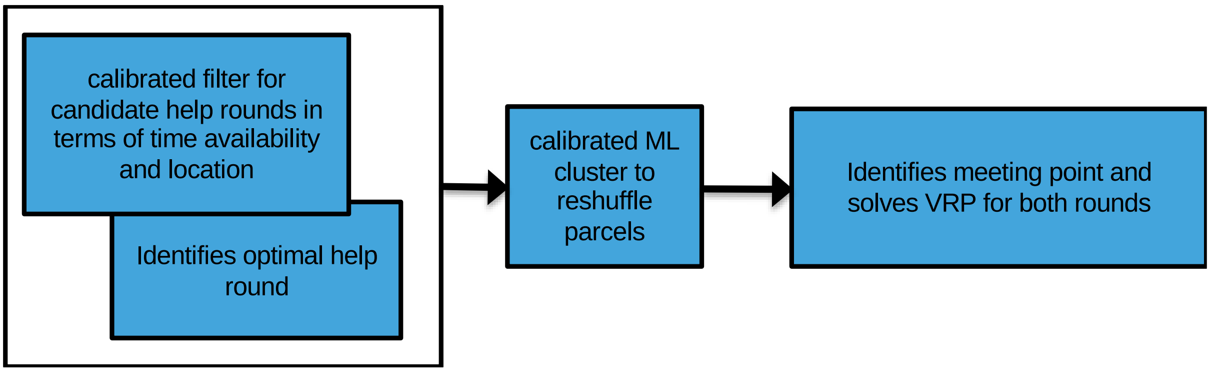

FIGURE 2 OVERVIEW OF THE DYNAMIC PARCEL RESHUFFLING MODEL

Delivery rounds, that are typically fully designed prior to initiating their implementation every day, consider the delivery locations, fleet availability (i.e., the number and capacity of delivery vehicles available) and local accessibility constraints such as Low Emissions Zones (LEZs) and delivery cut-off time. When delays arise, in order to expedite a late delivery round completion time, operators sent assistance vehicles, that share the delivery load. The visualisation of the delivery rounds (illustrated in Figure 3) enables the manual tracking of delivery progress, and the identification of severe delays, when a delivery round is considerably behind schedule. The red vertical line at 3pm captures the current time and enables progress inspection. For example, route C17 (first row) seems to be roughly on-time, while round C24 (last row) seems to be running slightly late.

FIGURE 3 EXAMPLE OF DELIVERY ROUNDS MONITORING DASHBOARD

As delivery round delays arise, the original planning and design of the rounds might need to be updated. This is because delivery operational constraints, such as delivery time windows (no deliveries past 9PM) and driver shift hours, cannot be violated. In such cases, a fleet operator tries to identify delivery rounds that might finish early or be ahead of schedule and dispatch them for helping the round running late. The process of identifying van availability, van suitability and then redesigning the delivery rounds, that involves identifying which parcels will be moved from the original van to the helping van, and where the two should meet for the parcel exchange will take place is currently undertaken manually.

The aim of DPRM contribution is to automate the process of identifying a vehicle that can share the delivery load with the late running vehicle, hereafter called the help vehicle and manage the operational parameters for materializing the exchange. This procedure involves identifying:

- which vans can be sent for assistance without inflicting severe delays in their delivery obligations,
- how many and which parcels require to be transferred from the late vehicle to the helping vehicle,
- a common meeting point for the two vans, and
- the dynamic redesign of the delivery rounds for both vehicles featuring a common meeting point.

The model is aimed to function as live tool for dynamically assisting and optimising same-day delivery. The tool is therefore developed as an online optimisation service that is computationally efficient and can assist decision making on the go.

5.2.3 Methodology

For identifying a help round the user can choose either a collaborative setting which assumes that all delivery vehicles are available despite their operator, or a company-silo setting which considers only the vehicles of a specific operator. Data on the estimated time of completion are collected (if possible) by the operator or else generated by the model using each vehicles pending deliveries centroid, and workload. The enhanced data are considered to identify the optimal helping vehicle based on a linear regression model that considers:

1. the distance from the delivery centroids of the late vehicle to any other delivery vehicle in the help vehicle candidates pool,
2. the time difference between the time of completion of each delivery vehicle in the help vehicle candidates pool to the deliveries cutoff time.

In the second step of the algorithm a K-means clustering algorithm is implemented to redistribute the parcel delivery jobs between the late running vehicle and the helping vehicle identified in the previous round. The output of the clustering algorithm is a tag for each node of the population, that corresponds to a unique delivery round. Each tag is then associated to each of the two delivery rounds, by using a linear optimization model that minimizes the number of parcels to be transferred to the help vehicle. The parcels are therefore, classified into the ones remaining in the late running round, the ones remaining in the help round, and the ones moving from the late running round to the help round.

In the final step of the algorithm a meeting point is identified that is associated to a narrow time-window for the two vehicles to exchange parcels with minimum waiting time. The functionality of the DPRM has been expanding in this step to account for live parking information where that is available. The meeting point necessitates proximity of the two vans in order to minimise the diversion required for including the meeting point in their route and sufficient parking space availability. The distances between all the pending delivery locations of the late running vehicle, and the pending delivery locations of the parcels remaining on the help vehicle are considered. The locations of the parcels moving from the late running round to the help round are excluded from this process, as prior to the exchange at the meeting point, they are loaded on the incorrect van. The two points with the closest distance are identified, and a nearby parking location with sufficient space for two vehicles is identified. The meeting point represents a location suitable for the two vans to visit, however there is no guarantee up to this point that the two vans arrive there simultaneously. To address this, a common time window is set on both vans for reaching the meeting point. Parking space availability is then assessed by connecting to the service that analyses the live feed from the cameras and by collecting the live parking spot availability information. This parking spot location is then added to the locations the late running and help vehicles require to visit associated with the predetermined time-window. A Travelling Salesman Problem with time-windows is then solved, including a common time window for reaching the meeting point.

5.2.4 Data Specification

The input data required to run the dynamic parcel reshuffling model, and the output data describing the results are given in Tables 7 and 8 respectively.

TABLE 7 INPUT DATA FOR THE DYNAMIC PARCEL RESHUFFLING MODEL.

Input Data	File type	Description
parcel_information	.xlsx	A list of address locations parcels to be delivered and the locations they are to be delivered to
parking_availability	.xslx	A table giving the number and location of available parking spaces.
vehicle_availability	.xlsx	A table giving the availability of each delivery vehicle.

TABLE 8 OUTPUT DATA FOR THE DYNAMIC PARCEL RESHUFFLING MODEL

Output Data	File type	Description
parcel_reallocation	.xlsx	Instructions to vehicle identifying meeting points, and the parcels to be reallocated for delivery.

6 ADV Routing Simulation Model

6.1 Motivation for the ADV routing simulator

To explore the acceptability of Automatic Delivery Vehicles (ADVs) by consumers, an integrated agent-based simulation model was designed and developed by NORCE. That model simulates consumer choices between the ADV service and home delivery options over time. If the ADV is chosen, the VRP module developed by SKEMA (*available in Deliverable 3.2*) computes the delivery times, percentage of total parcels delivered, average waiting time and the average queue length at each delivery point. It also computes the total distance travelled and the total emissions produced by the ADV during the delivery round. The benefit of this model is that it allows the LL to simulate the operation and acceptance of the ADV. The disadvantages of the model are that it does not allow for the possibility of the ADV to deviate from an optimized route. It also assumes that customers arrive to collect their goods at regular intervals and does not account for inhomogeneous arrival times.

6.2 Modelling Approach

The ADV routing simulator first computes the most efficient path for the ADV to take to reach all delivery points within the delivery time windows. Then, at each delivery point, a single-server queueing simulator is run to simulate the interaction of customers with the ADV. The output of the model includes: the time at which the robot arrives at each delivery point, the percentage of parcels successfully delivered, the average waiting time, and the average queue length at each delivery point. It also computes the total distance travelled, as well as the total emissions produced (in gCO2eq) during the delivery operation.

Furthermore, an assignment optimisation model has been integrated in the Helsinki LL in order to pre-sort the parcels to be delivered by the ADVs. As presented in *D1.1. URBANE framework for optimised green last mile operations*, the implementation of PI-inspired last mile deliveries involves the sequencing of the process by initially considering the more efficient vehicles. The algorithm considers the ADV routes and capacity and estimates the straight-line distance of each delivery point to its nearest ADV stop. Then a linear optimisation algorithm determines the maximum radius an ADV can serve before it reaches its capacity. A uniform catchment radius is considered for all ADV stops.

6.2.1 Data Specification

The input data required to run the ADV simulator model, and the output data describing the results are given in Tables 9 and 10 respectively.

TABLE 9 INPUT DATA FOR THE ADV ROUTING SIMULATION MODEL

Input Data	File type	Description
ParcelDemand	.csv	A list of parcels to be delivered and the locations they are to be delivered to
electricity_generation_breakdwn	.xslx	A table with parameters describing the different sources used to generate electricity, the emissions factor associated with each source.
robot	.xlsx	A table giving the speed of the robot, the battery capacity and the number of parcels it can delivery per minute.
Problem_input	.xlsx	A table detailing the earliest and latest arrival times at each destination node, the amount of time the robot waits at a node, and the number of customers arriving per minute at that node.

TABLE 10 OUTPUT DATA FOR THE ADV ROUTING SIMULATION MODEL

Output Data	File type	Description
Delivery_results	.xlsx	For each delivery point: the output gives the ADV's arrival time, total number of parcels successfully delivered, the average waiting time and the average queue length.
Total_emissions	.xslx	The total emissions (in gCO_2eq) during the delivery round
Total_distance	.xlsx	The total distance (in km) travelled by the robot

7 Cost-Benefit Analysis Tool

7.1 Motivation for the Cost-Benefit Analysis Tool

The aim of the tool is to consider the cost breakdown and overall financial performance of last mile and middle mile urban delivery operations and to enable the impact analysis of infrastructure investments and operational models. The CBA tool is a component of the URBANE Digital Twin (DT) platform and has been developed to connect to other tools and models on the platform. Its requirements and components are therefore aligned with the outputs of the predecessor models and the calculations are designed to fit in the context of URBANE project.

7.2 Overview of the Cost-Benefit Analysis Tool

The initial implementation of the Cost-Benefit Analysis (CBA) tool focuses on Bologna's LL and the assessment of infrastructural investments in association with operational adjustments for the utilization of parcel lockers and green last mile delivery. The DT runs a sequence of models for analyzing the operational performance of the LL including the "Collaborative delivery model" (CDM) presented in Section 4, that produces routing instructions for the middle and last milers and evaluates the distance each operator will cover. Other inputs utilized by the CDM include the vehicle type, the number of vehicles and the number of deliveries, which integrated with the CDM output of total distance travelled per operator are passed to the CBA tool.

Additional inputs that are required for performing the CBA calculations are collected through the DT interface and include the labor cost [per delivery], and the foreseen total investment cost. The CBA tool can optionally accept inputs on the fuel value, the number of deliveries per day per staff, and the annual discount rate.

The CBA calculations are divided into two categories. The first category focuses on the analyses of daily costs for staff and vehicle fuel. The second category extrapolates the daily costs to monthly and yearly cost benefit projections.

7.2.1 Category A Calculations: Daily Cost Estimation

The daily cost is estimated based on fuel and staff cost components. For the calculation of fuel/ energy cost, the total distance driven by the vehicles of each operator and their fuel type are considered. For the estimation of staff costs, the following assumptions are made:

- Each vehicle in the fleet is staffed by at least one person
- One person can deliver up to 120 parcels per day

Considering the total number of vehicles in the fleet and the total number of deliveries, the minimum staff and are estimated respectively. The largest of the two values is then chosen and multiplied by a daily work rate provided by the user through the UI. Currently the staff cost input is per delivery (rather than per day).

7.2.2 Category B Calculations: Monthly and Horizon Projections

The user is asked to provide an initial investment cost associated with the operational set-up that is examined in the analysis. The user optionally provides a planning horizon and an annual discount rate, that by default are set to five years and 3% respectively. An NPV (Net Present Value) calculation takes place in the CBA by considering discounted daily operational expenses.

The investment's break-even point in time is estimated by the CBA tool. To complement this metric, the break-even point calculation will be extended to estimate the units/ day that require to be delivered for a profitable daily operation as well as the total number of units sold for counterbalancing the initial investment. This is estimated by dividing the total fixed costs associated with production by the revenue per individual delivery minus the variable costs per unit. In this case, fixed costs refer to those that do not change depending upon the number of units sold.

Figure 4 illustrates an overall representation of the CBA inputs, calculations and processes. Further work components identified include:

- the consideration of equipment lifecycle to include the depreciated assets value in the NPV calculation,
- the consideration of fixed operational and maintenance costs associated to facilities and vehicles,
- the quantification of CO_2 emissions costs.

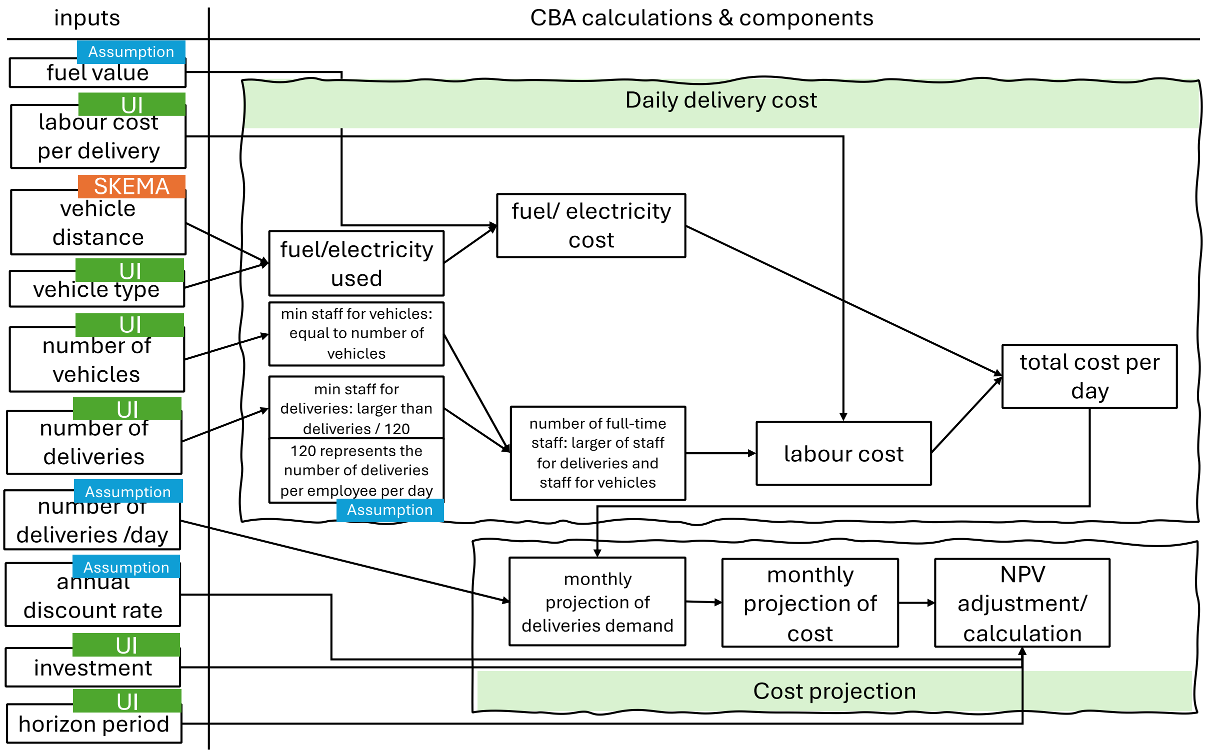

FIGURE 4 CBA TOOL CALCULATION PROCESS AND COMPONENTS

7.2.3 Data Specification

The input data required to use the CBA tool, and the output data describing the results are given in Tables 11 and 12 respectively.

TABLE 11 INPUT DATA FOR THE CBA TOOL

Input Data	File type	Description
Fuel_value	.csv	The cost of fuel/electricity used.
Vehicle_information	.xslx	The number and types of delivery vehicles used.
Delivery_information	.xlsx	The number and location of deliveries.
Problem_inputs	.xlsx	The annual discount rate, the total investment, and the horizon period.

TABLE 12 OUTPUT DATA FOR THE CBA TOOL

Output Data	File type	Description
Cost_projection	.xlsx	Projection of costs, financial impacts, NPV, and break-even points.

8 Case Studies examined in URBANE Wave 1 LLs

8.1 Bologna Living Lab

8.1.1 Motivations Behind Choosing Bologna LL

This living lab was chosen because it is in the process of implementing the infrastructure that will allow us to apply our collaborative model as well as the CBA tool. A few first and last mile operators have signed up to participate in the URBANE project, and micro-hub facilities have been installed.

8.1.2 Application of Collaborative Delivery Model in Bologna

We use historical data from partners in the Bologna LL regarding the location of deliveries and micro-hubs (for the list of datasets please refer to D2.3 Bologna Demonstrator). These data comprise the locations and number of deliveries carried out in the past.

Simulations and Results

We carried out a simulation for a single day of deliveries. Our simulation covered a scenario in which there are two last mile operators performing deliveries of fifty (50) packages. We compared the current delivery approach with our collaborative model. The figures and table below show that without collaboration, each last miler has to cover more distance than by using the results of the collaborative model. It can be seen in figure 5 that with collaboration, the delivery areas are split more homogenously among the last mile operators. Table 13 below shows the total distances and emissions from both the simulation. It can be seen that the use of the collaborative model resulted in a 10.65% reduction of distance travelled and CO2 emissions. We expect that even better reduction can be achieved if more last mile operators are involved.

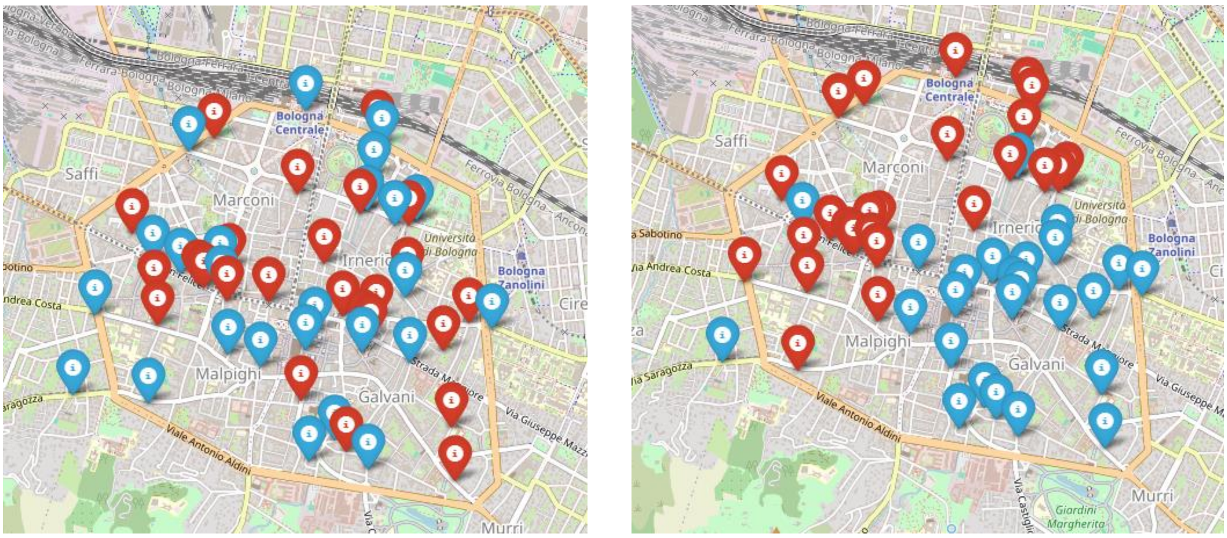

FIGURE 5 EVEN SPREAD OF DELIVERY LOCATIONS WITHOUT AND WITH COLLABORATION

TABLE 13 RESULTS OF COLLABORATION

	Without Collaboration			With Collaboration		
	Last Miler 1	Last Miler 2	Total	Last Miler 1	Last Miler 2	Total
Total distance (km)	15.02	17.57	**32.59**	12.45	16.84	**28.93**
Total CO2 emissions (gCO2eq)	299.55	350.49	**650.04**	248.37	335.97	**584.34**

8.1.3 Application of Cost Benefit Analysis Model in Bologna

By varying the parametres (such as number of micro-hubs, the number and type of delivery vehicles, and others), we can evaluate the short- and long-term horizon costs for each scenario. Figure 6 below shows an example of a cost projection over five years for a scenario with three micro-hubs, and a single LM using four EDVs.

FIGURE 6 COST-BENEFIT ANALYSIS SHOWING COST PROJECTION OVER

8.2 Helsinki Living Lab

8.2.1 Motivations Behind Choosing Helsinki LL

This living lab was chosen because it is in the process of implementing ADV deliveries, and the infrastructure that will allow us to apply our ADV model.

8.2.2 Application of ADV Routing Simulation Model in Helsinki

The Helsinki LL proposed testing the concept of micro-hubs in the city, specifically focusing on innovative delivery options such as robot deliveries using Autonomous Delivery Vehicles (ADVs), cargo bikes, and teleoperation. The development and use of the ADV routing simulator will enable the simulation of consumer behaviour when using the ADV service. It will also enable the follower LLs to simulate operations in their own cities and establish best practices for integrating these advanced delivery systems into their urban logistics networks.

8.2.3 Simulations and Results

The performance of the ADV was simulated over 31 days under various parcel demand and customer arrival rates. The analysis showed that successful delivery rates are dependent on the width of the time windows at each delivery point, as well as the ADV's waiting time at each delivery location. To achieve a high satisfaction rate for a given delivery scenario, the locations' time windows and waiting times should be optimized such that a high delivery rate is achieved while ensuring that the ADV is capable of operating for the required length of time. Please see Deliverable 3.2 Modelling Framework and Agent-Based Models for the full simulation results.

8.3 Valladolid Living Lab

8.3.1 Motivations Behind Choosing Valladolid LL

This living lab was chosen because the infrastructure that will allow us to apply our DPR and demand prediction models are in place. The implementation of the computer vision-based model that allows us to find and allocate free parking spots helps facilitate the use of the DPR model in this LL.

8.3.2 Application of the DPR model to the Valladolid LL

In the context of the Valladolid LL, two extensions have been implemented to the DPRM. The first extension is associated to overcoming the limited availability of real-time parcel delivery data by implementing a data generation and delivery simulation. The second extension is associated to accessing and integrating live parking location data. In Valladolid live cameras integrated with a computer vision algorithm track parking locations availability and the data are available through a software interface. The data generation extension can handle multiple background processes that are associated to the implementation of delivery rounds. The model produces randomised delivery location data within a confined polygon. This deliveries volume and the location are inputs to the model and can be adjusted by the user. The location can be communicated either as a string of the city name or a shapefile as illustrated in **Σφάλμα! Το αρχείο προέλευσης της αναφοράς δεν βρέθηκε.** for Valladolid city. Assuming the availability of a distribution depot, and a known number of delivery vehicles, a solution to the capacitated vehicle routing problem can be obtained. Then a delivery delay's simulation can be called that automatically simulates the implementation of delivery rounds at one-minute intervals, estimates the progress and monitors traffic delays. The simulation raises a flag whenever a delivery vehicle is running late and cannot complete its scheduled deliveries.

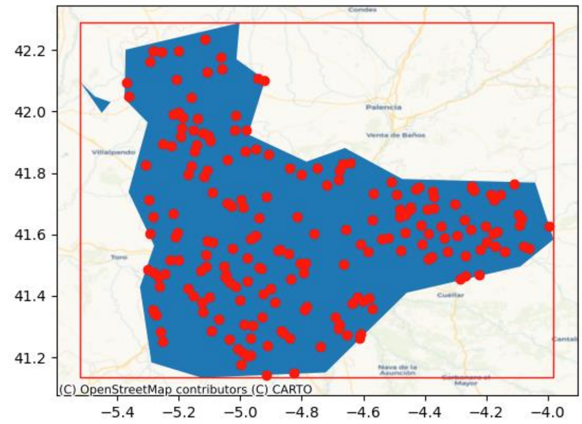

FIGURE 7 RANDOM DEMAND GENERATION (FOR 200 DELIVERIES IN VALLADOLID)

The DPRM has been enhanced to also consider the data in determining an optimal meeting point for the two vehicles. The identification of the meeting point is a particular challenge as it requires sufficient space for both vehicles to briefly park and exchange parcels. If there isn't sufficient space for both vehicles to park next to each other the process might require significant effort and time, defeating the purpose. Once the DPRM is executed an approximate location and time of the meeting point are estimated based on the known delivery locations, and the routing sequence. More specifically the location describes for each round the point of the least distance to the other vehicles route. As the vehicles approach each other the parking space availability is examined. After filtering for sufficient space (at least two parking spots are required), a set of five candidate meeting point locations are identified and ranked based on average distance to both vehicles. Then, the live data on parking space availability are collected and the highest ranked available space is set as the meeting point for the two vehicles.

Simulations and Results

The DPRM algorithm was applied on a simulated dataset in Valladolid for average and high demand cases, as well as for single company and collaborate help vehicles pools. Although the model has been assessed quantitatively, the results are presented in a qualitative manner (see Figure 8) as performance is closely associated to delivery volume and the vehicle fleet size of each operator. The qualitative assessment of the DPRM captures two performance metrics:

- Feasibility: expedite delivery of the late running vehicle to enable round completion prior to the delivery cut-off time.
- Good solution quality: the completion of the delivery rounds without additional flags raised by the simulation for the two delivery vehicles.

The DPRM single operator scenario assumes that each last mile distributor operates in isolation and parcel reshuffling is possible between the same company's vehicles. The collaborative help pool scenario assumes that last mile distribution companies can collaborate. The tool was able to perform live optimisation of the results and successfully expedite deliveries in all the cases examined. Good quality help was also offered in all cases except the single operator extreme volume case. In this scenario most help vehicles were found to have busy schedules timewise, which had a negative impact on the quality of help vehicles identified (either too far or with marginal spare time). Although amended instructions were delivered by the DPRM, when the simulation continued further, delivery delays were identified for the two vehicles involved indicating a low-quality result. The problem was not present in the extreme volume with collaborative pool scenario where good quality help was provided. It was also observed that in light to medium volume the delivery completion was not significantly improved when collaborative pool vehicles were made available. This indicates that a sufficiently good solution was already present in the single operator pool.

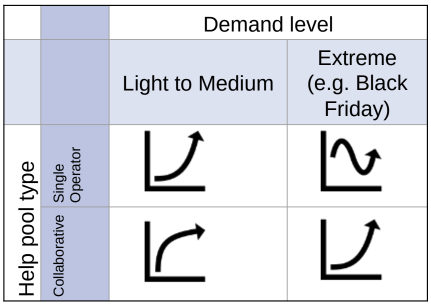

FIGURE 8 DPRM QUALITATIVE PERFORMANCE

The DPRM was overall found to positively contribute to live optimisation of delivery vehicle rounds when delays beyond a cutoff time.

8.3.3 Application of the demand prediction model to the Valladolid LL

Figure 9 below shows an example output prediction of the forecast. The bars shown in blue signify the estimated number of parcels to be delivered by bike, while those shown in red signify the estimated number of parcels to be delivered by car. These values are then used to forecast the number of bikes and cars to be put into service.

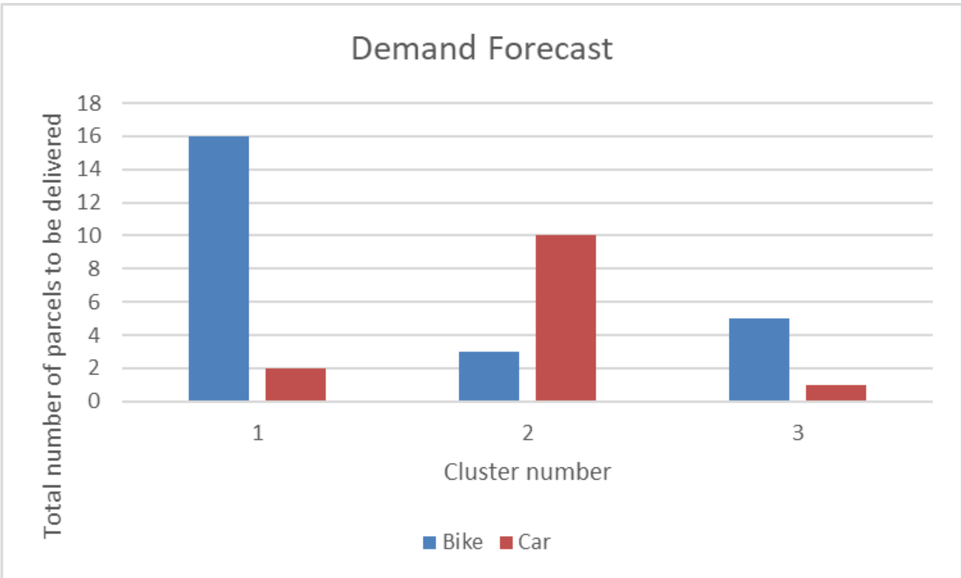

FIGURE 9 NUMBER OF FORECASTED DELIVERIES

9 Discussion

The development of AI-driven models and their implementation on real-world datasets uncovered multiple insights. From a modelling standpoint, stakeholders' participation and data availability are fundamental. Stakeholders, i.e. city authorities and last mile service providers, play a key role in shaping abstract models for optimizing delivery logistics operations. Understanding and integrating stakeholders' goals in the decision process affects how models should be designed. Models require data; thus, the availability of data is primordial. The models developed have been adjusted to work with the data made available by project partners and to align with LL's preferences.

While more simulations need to be conducted, the initial results are promising. It is envisaged that as time progresses and more data is collected, these models which have been implemented can be further refined. The models developed under Task 3.5 are designed in such way that are easily transferable to the next waves of living labs.

9.1 Strategic Recommendations to Real-life Stakeholders

The following recommendations are considered important for the improvement and implementation of these models:

- Data collection and availability: It is essential that stakeholders put in place data collection strategies to ensure that the relevant data concerning transportation in the last mile is collected and stored appropriately. This data should also be easily available to partners so that continued modelling and analysis can occur.
- Incentivization: Governmental or regulatory stakeholders at city or regional level should find a way to incentivize collaboration among competing partners, as the modelling results indicate both environmental and financial benefits.

9.2 Reusability of Developed Models in Wave 2 and afterwards

The above models have been developed to be as flexible as possible. Future living labs who wish to use these models simply must provide data in the correct formats. In cases where future living labs have needs that are slightly different from those addressed by the above models, it will be possible to either make minor alterations to these modes or combine models to satisfy these needs. Furthermore, the models and the algorithms designed to solve the optimization problems are city-agnostic and can thus be used in other urban environments than those that were used in the simulations. All code is available at the https://github.com/adefajem/URBANE-SKEMA-v2 and https://gitlab.com/urbane-horizon-europe/model-library/parcel-reshuffling repositories.

10 Conclusions

Five models have been presented in this document – Collaborative Delivery, Demand Prediction, Dynamic Parcel Reshuffling, ADV routing and Cost Benefit Analysis Tool. These models contribute to multiple facets of last mile delivery logistics and have been developed to make last mile logistics greener. The Collaborative Delivery model proposes a novel framework to coordinate the operations of first and last mile delivery service providers. The model takes into account the preferences of delivery service providers and assigns parcels to satellite hubs and last milers in such a way that emissions are minimized throughout the distribution network. A data-driven optimization approach has been developed to provide a scalable solution method to solve this challenging problem. Results show that we are successful in reducing the distance travelled and total CO_2 emissions. Additionally, we were able to reduce the overlap of last mile operators in a geographical area. This has the benefit of also reducing noise and congestion. The Demand Prediction model focuses on forecasting customer demand using machine learning based on historical delivery data. The Dynamic Parcel Reshuffling model aims to optimize delivery operations by determining meeting points for parcels exchange among delivery vehicles. This model uses supervised and unsupervised learning to predict optimal courier to request re-assignments. The ADV Routing Simulation model, developed in collaboration with NORCE, is used to simulate consumer interactions with ADVs. It evaluates delivery times, success rates, emissions, and customer queue lengths, providing insights into the potential adoption and performance of ADVs in urban settings. The CBA tool assesses the financial and operational aspects of last-mile and middle-mile urban deliveries. This tool is particularly focused on Bologna's green delivery initiatives, calculating daily costs, long-term financial impacts, and estimating break-even points for delivery operations.

The future applications of these models are extensive. They could be used in the Wave 2 LLs, or adapted for use in other cities, each with unique delivery challenges, or expanded to integrate with emerging technologies like drone delivery and AI-driven logistics management. Additionally, as consumer behaviours and urban landscapes evolve, these models can be recalibrated to meet new demands and optimize efficiency further. However, there are limitations to consider. The effectiveness of these models is heavily reliant on the quality and availability of real-time data, which can be challenging to obtain consistently.

These five models work together to enhance the sustainability of last mile delivery operations. Demand prediction and dynamic re-assignments algorithms are key ingredients of modern last mile logistics and ensure that planners and planning models are informed with appropriate data. It is envisaged that the implementation of our models can make last mile deliveries greener and cities more liveable.

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