D3.2: Modelling Framework and Agent-Based Models

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URBANE

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Executive summary

The context of the URBANE project is given by the need to reduce the negative effects of the recent strong increase in urban freight transport, due to e-commerce and the ensuring growth of parcel delivery services. The final stage in the parcel delivery process, known as the last-mile, involves delivering the package to the ultimate recipient. The service requirements will depend on the type of product and type of transaction, business-to-consumer (B2C), business-to-business (B2B), or consumer-to-consumer (C2C). Last-mile logistics usually encompasses a large network of interrelated participants, each with numerous interactions and mutual dependencies.

Within this network, every stakeholder makes choices based on their own limited information, aiming to optimise their individual benefits, often without considering the efficiency of the entire system. This lack of coordination often leads to low utilisation of services and heavy delivery traffic in residential neighbourhoods. Stakeholders can also be nudged to work together, however, in smart, collaborative last-mile delivery systems, which is the subject of URBANE.

In the URBANE project, various innovations are evaluated in urban living labs and with quantitative models of the urban freight system. The objective of Task 3.4 is to assess how consumers choose a delivery method including how decisions evolve in the social environment of consumers. To this end, we linked the two agent-based modelling (ABM) tools, HUMAT (NORCE) and MASS-GT (TUD), as a high-level agent-based modelling framework to support evaluations. Parallel to defining the dedicated modules of this modelling framework and the necessary input and output data, interconnections were defined between them. During this process, we resolved issues related to suitability of input/output data and risk of creating incompatibility. We reimplemented and tested HUMAT in Python for its interoperability with MASS-GT.

Discussions with the living labs and other URBANE modelers showed that we can model case studies for two living lab cities: Thessaloniki (GR) and Helsinki (FI). These cases focus on consumer acceptance behaviour in relation to parcel locker (PL) delivery and autonomous delivery vehicle (ADV) delivery, respectively. However, since MASS-GT is not fully capable of simulating the ADV delivery, we decided to use also the VRP (SKEMA) tool.

The resulting innovations developed in Task 3.4 are (1) a generic functional architecture of the modelling framework, straightforward to calibrate for new cases, and (2) calibrated models which are transferable towards similar case studies of other living labs. Through the integration of the HUMAT, MASS-GT and VRP tools, the study represents a significant advancement in understanding and optimising last-mile delivery systems. It allows to examine the social-behavioural aspects of various innovative city logistics scenarios, providing insights into consumer decision-making processes for different delivery methods.

By addressing challenges in data compatibility and interoperability, and through close collaboration with living labs and modelers, we have developed a versatile and scalable modelling framework. This framework not only effectively assesses consumer behaviour in diverse scenarios like parcel lockers, and ADV deliveries in Thessaloniki (GR) and Helsinki (FI), but also establishes a foundation for future exploration and application in other urban contexts.

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Glossary of Terms and Acronyms

TABLE 1 GLOSSARY OF ACRONYMS AND TERMS

Acronym / Term	Description
ABM	Agent-based Model
ADV	Autonomous Delivery Vehicle
B2B	Business-to-business
B2C	Business-to-consumer
C2C	Consumer-to-consumer
CO2	Carbon dioxide
DT	Digital Twin
EU-SILC	European Union Statistics on Income and Living Conditions
EUROSTAT	European Statistical Office
FI	Finland
GR	Greece
KPI	Key Performance Indicator
LL	Living Lab
LMD	Last-Mile Delivery
MASS-GT	The Multi-Agent Simulation System for Goods Transport
OO	Object-Oriented
PC4	4-digit postcodes
PL	Parcel Locker
PI	Physical Internet
UCC	Urban Consolidation Centre
VRP	Vehicle Routing Problem
VKT	Vehicle-kilometres

1 Introduction

The URBANE project, a pioneering initiative under the Horizon Europe framework, aims to develop a Replication and Scale up Model for the wide and fast replication of successful smart green last-mile delivery solutions. It aims to revolutionise urban logistics through the development and integration of innovative technologies and methodologies. This document focuses on Deliverable D3.2: Modelling Framework and Agent-based Models, playing a crucial role in realising URBANE's ambitious objectives. Positioned within Work Package 3 (WP3) and more specifically Task 3.4, this deliverable plays a critical role in advancing the project's overarching goals of enhancing urban logistics efficiency, sustainability, and stakeholder engagement.

WP3, dedicated to the development of models and services, serves as the technological backbone of the URBANE project. It aims to harness the power of artificial intelligence, agent-based modelling, digital twins (DTs) and blockchain to create a suite of tools and models that facilitate smarter, greener, and more efficient urban logistics solutions. By focusing on the seamless integration of innovative logistics models and the digital transformation of urban freight systems, WP3 addresses the pressing need for sustainable urban logistics practices.

Task 3.4 concentrates on the development and application of a complex modelling framework alongside agent-based models (ABMs). This task is pivotal in simulating and analysing the complex interactions between consumers, and service providers in urban logistics. Through the synergistic use of the HUMAT architecture and the Multi-Agent Simulation System for Goods Transport (MASS-GT) model, Task 3.4 offers nuanced insights into the diffusion of innovative logistics solutions, their acceptance within communities, and their impacts on businesses. This comprehensive approach not only aids in understanding the dynamics of delivery demand and service supply but also in exploring innovative logistics initiatives from a bottom-up perspective. It considers the individual characteristics of users and their collective influence on last-mile delivery (LMD) demand.

This deliverable encapsulates the agent-based modelling activities designed to yield strategic recommendations for stakeholders in LMD and the implementation of Living Labs' Digital Twins with two selected real living lab (LL) cases (Thessaloniki LL and Helsinki LL). These LLs are selected based on their suitability for studying consumer behaviours in LMD systems. This deliverable elaborates the interconnections and complementarities between the HUMAT and MASS-GT models, emphasising their roles in calibration, validation, and simulation within urban logistics scenarios. The deliverable's focus on ABMs is instrumental in providing a deep understanding of social-behavioural dynamics and fostering citizen participation in sustainable city logistics processes.

D3.2 is not an isolated entity but a fundamental component that interlinks with various aspects of the URBANE project. By offering a robust and modular modelling framework and advanced ABMs, it directly contributes to the project's vision of creating a scalable, replicable, and sustainable urban logistics ecosystem. The insights derived from these models inform the development of policies, strategies, and innovations across URBANE, ensuring that the project remains aligned with its goals of efficiency, sustainability, and stakeholder engagement.

In summary, “Deliverable D3.2: Modelling Framework and Agent-based Models”, within the ambit of WP3 and Task 3.4, is crucial for advancing URBANE's objectives. By leveraging sophisticated modelling techniques and agent-based simulations, it provides the necessary analytical foundation to navigate the complexities of urban logistics, ultimately contributing to the project's success in fostering sustainable urban environments.

1.1. URBANE Outputs Mapping to GA Commitments

In this subsection, we provide a table that outlines the direct correlation between the deliverable's contents and the requirements set forth by the work package and tasks. It summarizes how Deliverable D3.2 satisfies the specific objectives and technical expectations of the URBANE project, particularly within the context of Work Package 3 and Task 3.4.

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

URBANE GA Item	URBANE GA Item Description	Document Chapter(s)	Justification
DELIVERABLE			
D3.2 Modelling Framework and Agent-Based Models	*The deliverable encompasses the agent-based modelling framework and specific models tailored for the project's living labs.*	*All the D3.2 Sections.*	*The current deliverable describes the agent-based modelling framework used for modelling last-mile delivery systems (Chapter 5) and the dedicated agent-based models for the selected Living Labs (Chapter 6), that have been developed under Task 3.4.*
TASK			
ST3.4.1 Modelling Framework	*The objective of this subtask is to map the objectives, requirements, inputs, and outputs of the ABM applied and developed within URBANE.*	*Section 5*	*The deliverable details the objectives, requirements, inputs, and outputs of the ABM, directly aligning with the expectations for ST3.4.1 by mapping out the modelling framework.*
ST3.4.2 Calibration and validation of ABM	*Calibration and validation of ABM with the use of data collected and prepared in T2.1, T3.1 and T3.3.*	*Section 6*	*It provides insights into the calibration and validation processes of the ABM, as stated in ST3.4.2, leveraging requirements and data from various sources within the project to refine the model's accuracy.*
ST3.4.3 In-silico experimentation	*In-silico experimentation with counter-factual scenarios of possible strategies increasing innovation uptake.*	*Section 7*	*The deliverable will later include results from in-silico experimentation, showing how the ABM can predict the impact of various strategies, which meets the deliverable's purpose as per ST3.4.3.*

1.2. Deliverable Overview and Report Structure

This document is organised as follows. Section 2 gives background information about LMD systems. Section 3 presents the state of the art for modelling LMD systems. Section 4 describes the theory (i.e. agent-based modelling) and the tools we used in this study (i.e. HUMAT, MASS-GT and VRP). Section 5 identifies our integrated modelling framework dedicated to simulating and assessing how consumers decide and how their decisions evolve in their social environment by considering various delivery options in an LMD system. Section 6 shows the effectiveness of our integrated modelling framework through three agent-based models calibrated for two real case studies, namely for Thessaloniki LL and Helsinki LL. Section 7 presents simulations and their results. Section 8 provides an overall discussion and Section 8.1 provides strategic recommendations for real-life stakeholders. Finally, Section 9 concludes the document and Section 10 presents the future work.

2 Last-Mile Delivery Systems

The last-mile refers to the final leg of the delivery operation through which the package is delivered to its final recipient (i.e., consumer). The dynamics of LMD demand vary across business-to-consumer (B2C), business-to-business (B2B), and consumer-to-consumer (C2C) purchases. In B2C scenarios, where businesses directly serve end consumers, there is a growing expectation for fast and reliable deliveries, primarily driven by the growth of e-commerce. On the one hand, B2B deliveries involving businesses serving other businesses often entail larger and more complex shipments. On the other hand, C2C interactions, typical in peer-to-peer marketplaces, present a unique set of challenges as individuals engage in the exchange of goods. This requires flexible and decentralised last-mile solutions. Meeting the diverse demands of these business models is crucial for optimising last-mile logistics operations and ensuring customer satisfaction.

The rapid growth in LMD demand causes several externalities in urban areas, including increased traffic congestion and a rise in noise and visual pollution. The rapid growth strains the existing infrastructure, causing inefficiencies in delivering parcels and challenges in meeting customer delivery needs. Customers demand high service quality within a minimum amount of time, which leads to additional pressure on last-mile logistics service providers (Kader, Rashaduzzaman, Huang, & Kim, 2023). Due to several inherent factors such as delivery failure, low empty trips and number of van stops, LMD services become the most expensive and most polluting layer of the supply chain (Brown & Guiffrida, 2014; Gevaers, Van de Voorde, & Vanelslander, 2011).

Last-mile logistics systems involve various interconnected actors with multiple interactions and interdependencies. Each actor within such systems makes decisions based on limited knowledge to maximize their own interests, disregarding the overall system efficiency (Anand, 2015; Robenek, Maknoon, Azadeh, Chen, & Bierlaire, 2016). Therefore, despite the shared objective of transferring goods, conflicts of interests may arise among stakeholders.

In the specific case shown in Figure 1[1] suppliers are the stakeholders responsible for providing goods (Tapia & Kourounioti, 2021). They aim to maximize profits by managing transportation and inventory costs. As another critical actor, retailers place orders with suppliers and handle the storage and delivery. Retailers hold considerable influence in urban freight logistics because they determine the quantity of delivery, selling price of goods, and stock policy (Anand, 2015).

Consumers initiate the process by placing orders, thus creating freight demand. They typically prioritise short delivery times and aim for minimal product and delivery costs (Stathopoulos et al., 2011). Additionally, recipients specify the quantity of goods, delivery location, and delivery date (Anand, 2015; Stathopoulos et al., 2011). Given the complex nature of last-mile logistics, recipients' decisions contribute to a more personalised yet expensive delivery process.

Carriers transport the goods to consumers, retailers, or urban consolidation centres (UCCs) (Anand, 2015). They prefer to execute the service at a low cost by maximising vehicle load factors of delivery. Carriers make several choices, such as determining the route, transport vehicles, and delivery time. While

[1] This deliverable focuses specifically on last-mile logistics. In a broader supply chain context, including a first-mile logistics service provider is necessary. Moreover, the figure requires relevant modifications when representing different business models (e.g., assuming the existence of urban consolidation centres, direct shipments from suppliers instead of e-retailers, or omnichannel retailing).

they make their decisions, carriers must meet the requirements of customers/retailers. Additionally, carriers' vehicle choices must comply with the public authority's regulations.

Public authorities plan, organise, and control the policy measures by setting regulatory measures. These regimes cover the necessity of building new infrastructure, efficient usage of existing infrastructure, rules about access to the city centre, and other policies related to land use and environmental protection. Regulations that public authorities apply have essential impacts, e.g., on the locations of the transported goods and UCCs, appropriate loading and unloading times, or mandating types of vehicles that carriers are obligated to use.

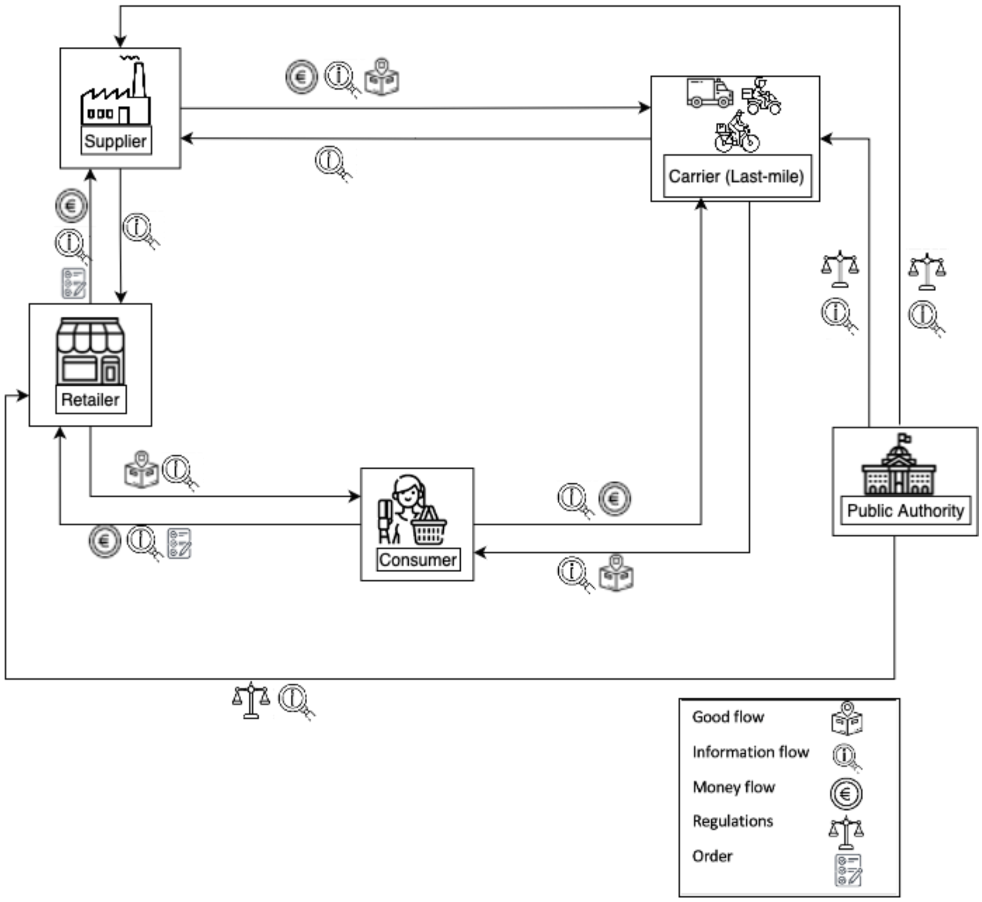

FIGURE 1 MODEL OF TRADITIONAL LAST-MILE LOGISTICS

The literature increasingly emphasises novel and innovative LMD services. These services encompass a variety of options, such as parcel lockers (PLs), which is also referred to as self-collection points (Wang, Yuen, Wong, & Teo, 2018; Yuen, Wang, Ng, & Wong, 2018), advanced technology-driven services (Cai, Yuen, Xie, Fang, & Wang, 2021), omnichannel retailing-enabled choices like click-and-collect services (Vyt, Jara, Mevel, Morvan, & Morvan, 2022) and crowdshipping (Rougès & Montreuil, 2014). These innovations complement the conventional delivery methods offered by commercial courier companies, as discussed in Agatz, Campbell, Fleischmann, and Savels (2008), covering a variety of common and distinctive characteristics.

LMD services focus on improving the efficiency and convenience associated with LMDs (Kader et al., 2023). In the literature, these aspects are studied in the context of PLs (Tiwapat, Pomsing, & Jomthong, 2018) and crowdshipping (Macrina, Pugliese, & Guerriero, 2020). These services offer alternatives to the conventional delivery method, which can be costly (Agatz et al., 2008), less convenient for consumers due to failed home deliveries (Edwards, McKinnon, Cherrett, McLeod, & Song, 2010) and negatively affect the environment (Manerba, Mansini, & Zanotti, 2018).

A central theme among delivery services is prioritising consumer preferences (Agatz et al., 2008). They are designed to enhance consumer experience, allowing them to decide when and where to receive their orders, thus tailoring the delivery experience to individual needs. Moreover, delivery methods like PLs empower consumers to actively engage in the LMD process by collecting their ordered items from a designated location (Wang, Wong, Li, & Yuen, 2021). With crowdshipping, consumers even become an occasional carrier for delivering parcels for others (Le, Stathopoulos, Van Woensel, & Ukkusuri, 2019).

Many of the approaches, including click-and-collect and using PLs, actively address the environmental impact of last-mile logistics (Edwards et al., 2010; Manerba et al., 2018). One of the features of PLs and click-and-collect points is their accessibility and flexibility (Jara, Vyt, Mevel, Morvan, & Morvan, 2018; Milioti, Pramatari, & Kelepouri, 2020; Vakulenko, Hellström, & Hjort, 2018). These services allow consumers to collect their orders from secure and strategically located lockers, often in urban areas and transport hubs. They also serve as drop-off points for returns.

Cutting-edge technologies are an integral part of all these delivery methods. They leverage various technological tools, whether through the implementation of online platforms, mobile applications, or the adoption of advanced innovations like drones and robots. Technological integration enhances the overall delivery process and keeps these methods in line with evolving consumer expectations in the digital age. While traditional home delivery remains a preferred option due to the direct-to-door service for its users, advanced technology-driven delivery services such as autonomous LMD, drones, and delivery robots emerge for their innovation and futuristic approach.

In summary, while LMD methods share the goal of improving the LMD experience, they have distinctive features and characteristics that cater to different consumer preferences and logistical challenges. Each method offers unique advantages and addresses specific aspects of the delivery process, making them suitable for different scenarios and consumer needs.

3 Existing Last-Mile Delivery Modelling Approaches

Urban freight transport, comprising first-mile and last-mile logistics systems, possesses unique features and considerations that differentiate it from national or global freight transport systems. These include shorter distances, integration with first-mile transport, varying commodity types, and the competition for urban space. Consequently, modelling LMD is challenging. Within the domain of last-mile logistics, a diverse array of methodologies has emerged for modelling purposes at various levels and for different objectives. From a broader perspective, city logistics models serve two primary functions: (1) descriptive and (2) prescriptive (Tavasszy & de Bok, 2023).

Descriptive models explain how goods delivery activities function within an urban context. They aim to support the evaluation of economic, environmental, and societal impacts of LMD. Descriptive models include stakeholder analysis (Kiba-Janiak, Marcinkowski, Jagoda, & Skowrońska, 2021), understanding the interrelation between last-mile logistics entities (Harrington, Singh Srai, Kumar, & Wohlrab, 2016), and statistical models such as discrete choice models. The models may include optimisation to describe underlying rational decision-making behaviour of the stakeholders.

Prescriptive models aim to design optimal networks to enhance efficiency of LMD activities in urban areas, by employing operations research methods. These models include optimisation studies sometimes in combination with simulation approaches.

One of the challenges in LMD models is ensuring their reproducibility in diverse contexts. Additionally, these current models neglect to consider the interdependencies among activities or processes due to their lack of time dependence. ABM presents a distinctive approach that holds promise in addressing various problems in the realm of LMD systems, surpassing the limitations of traditional methodologies (Macal, 2016). However, determining the requisite level of precision and generalizability in developing an ABM system to fully exploit the advantages of agent technology poses a significant challenge. While ABMs hold promise to address problems of urban freight transport (Anand, 2015), determining the requisite level of precision and generalisability in developing an ABM to fully exploit the complex behaviour of the stakeholders poses a significant challenge. Still many models neglect to consider the interdependencies among activities and processes, due to their lack of time dependence and ignorance of social dynamics in communities and business ecosystems (Cebeci, de Bok, & Tavasszy, 2023; Zenezini, 2018).

4 Theory and Tools of the Study

For reproducing the behaviour consumers in LMD systems as a simulation and examine various hypothesis related to their decisions, we have opted for the agent-based modelling techniques (Section 4.1). Additionally, we have also selected dedicated tools for socio-cognitive agent-based modelling (Section 4.2), modelling freight transport (4.3) and modelling vehicle routing (4.4).

4.1. Agent-based Modelling (ABM)

Simulation models serve as invaluable tools for assessing strategic decisions in freight transport policies. However, the limitations of many operational models become apparent as they often lack the necessary behavioural elements to simulate the impacts of logistic services, policy measures, or planning scenarios (de Bok & Tavasszy, 2018). Urban logistics, such as LMD systems, are so called complex adaptive system (CAS), since they consist of interconnected social, ecological, and technical system element that interact with each other in a seemingly disorderly manner, resulting in a robust organisation (Ladyman et al., 2013[2]). System changes are emergent, which means that they are arising from the interplay between micro-level and macro-level factors. Driven by feedback loops and characterized by non-linear changes, these systems exhibit a capacity for self-organization (Carmichael & Hadžikadić, 2019[3]). It is particularly challenging to address problems occurring in a CAS because its behaviour is not governed by a central planner but shaped by evolving individual processes that change over time. To analyse and understand the dynamics of such complex systems effectively, a one-size-fits-all approach is insufficient. Instead, we require a flexible, context-specific, and multi-level approach that can comprehensively represent all kind of causal relationships.

Agent-based modelling (ABM) is the most suitable approach to represent and analyse CAS, as it captures fundamental social structures and the emergence of group behaviours, offering valuable insights into the complexity of urban logistics as CAS. ABM describes dynamics of socio-technical systems using computer simulations. It involves constructing artificial worlds consisting of multidimensional heterogeneous agents, which represent actors in the social world, and a defined environment in which these agents operate. Agents in ABM are reasoning, proactive and autonomous, allowing them to interact and perceive their artificial world dynamically (Gilbert & Troitzsch, 2005). A key feature of ABM, as highlighted by Epstein (2008) and (Gilbert, 2019), is its micro-level explicitness. This characteristic compels the modeler to accurately represent real-world processes.

A significant aspect of ABM is its capacity for in-silico experimentation through simulations. As Miller and Page (2009) noted, during these simulations, agents interact based on a set of predefined rules. These interactions, occurring within the defined environment, lead to emergent phenomena. Moreover, many simulation runs can be computed, and systematic variations allow for experimenting with population characteristics and policy interventions. In essence, an agent-based modelling can act as a virtual laboratory, enabling researchers to simulate and analyse emerging patterns and the dynamic interplay among agents (Szczepanska, 2023).

When simulating ABMs, we follow two phases: the setup and the execution phase. During the setup phase, we inform the model with data from various input files, incorporating population statistics, survey

[2] https://doi.org/10.1007/s13194-012-0056-8.
[3] https://doi.org/10.1007/978-3-030-20309-2_1.

data, geo spatial information, to initialize a specific scenario. Following the setup, we iteratively execute the main model loop activating the agent population in a random order over a given amount of timesteps.

4.2. HUMAT

Overview

HUMAT is an advanced socio-cognitive agent-based modelling architecture. It creates artificial populations where individuals possess dynamic beliefs about behaviours and social networks, facilitating communication. In simulations, these individuals make decisions on delivery choices influenced by personal beliefs, share information within their networks, and respond to societal norms. HUMAT integrates theories from cognitive, social interaction, and network perspectives, offering a comprehensive framework. This framework links motivations (like experiential, social, and value-based needs) with social cognition (understanding others), decision-making, and networked communication.

Originally developed for simulating innovation adoption in urban settings (Antosz et al., 2019), HUMAT has been applied to diverse empirical contexts. These include simulating the effects of closing a park to car traffic, engaging in heat network projects, creating transit-traffic-free local city blocks, and sustainable energy transitions on islands. More recently, HUMAT has expanded to model decision-making in fear-inducing situations to explore opinion dynamics and vaccination rates during the COVID-19 pandemic ((Antosz, Shults, Puga-Gonzalez, & Szczepanska, 2022) Li & Jager, 2023). The latest advancement is its integration into the URBANE project, which utilizes a platform independent variant of the HUMAT architecture (Gürcan, Szczepanska, & Antos[i]z, 2024[4]).

HUMAT consists of a collection of software agents, known as humats, that together create a synthetic population interconnected through social networks. Each humat agent holds a unique set of beliefs that define its worldview. These beliefs are influenced by a blend of experiential, axiological, and social needs, collectively referred to as motives that drive behaviour. When a humat encounters a choice with an alternative characterized by both positive and negative aspects, it experiences cognitive dissonance, a state of mental unease. This discomfort drives the agent to engage in information exchanges within its social network, seeking to achieve cognitive consistency, as illustrated in Figure 2. In these exchanges, humat either communicates its beliefs through signalling, attempting to persuade others to adopt its viewpoint, or it seeks alignment with its peers' beliefs through inquiry. Though actively engaging in processing and exchanging information the humat agent forms opinions which leads to different levels of satisfaction regarding the various choice – alternatives available to it. As detailed in Antosz et al. (2022), humats make decisions by evaluating the advantages and disadvantages of various choices against their motives, thereby forming expectations about the potential satisfaction from each decision.

[4] https://ssc23-sphsu.online/wp-content/uploads/2023/09/SSC2023_paper_58.pdf

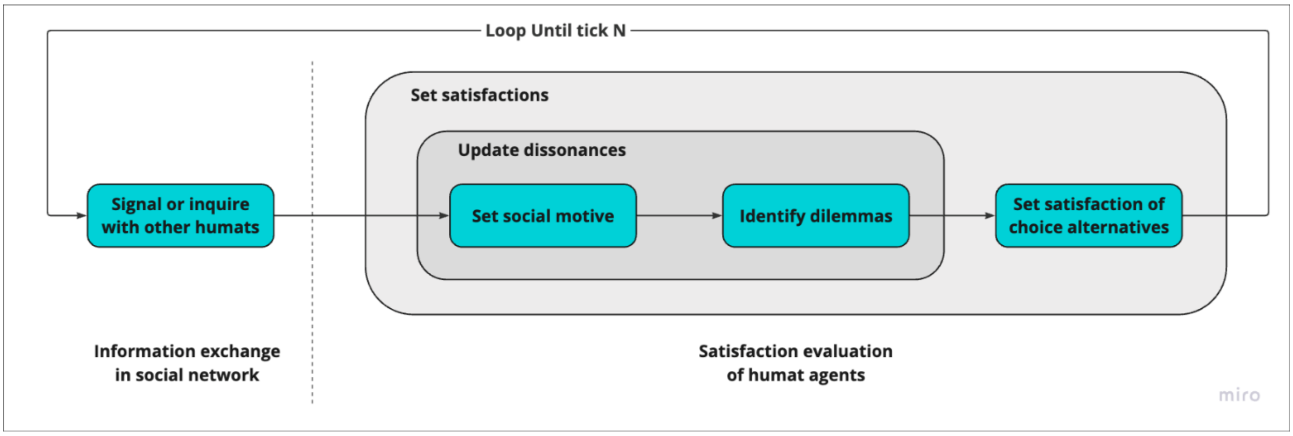

FIGURE 2 SIMPLIFIED CONCEPTUAL MODEL OF HUMAT'S DECISION MAKING & OPINION DYNAMIC MODULE

Architecture

The *Decision Making & Opinion Diffusion* module of the HUMAT model is instantiated as illustrated in Figure 3. This module operates by processing four key inputs: (1) Synthetic Population Data, (2) Fulfilment Data, (3) Parcel Demand Data, (4) Social Network Nata, and (5) Consumer Motives Data.

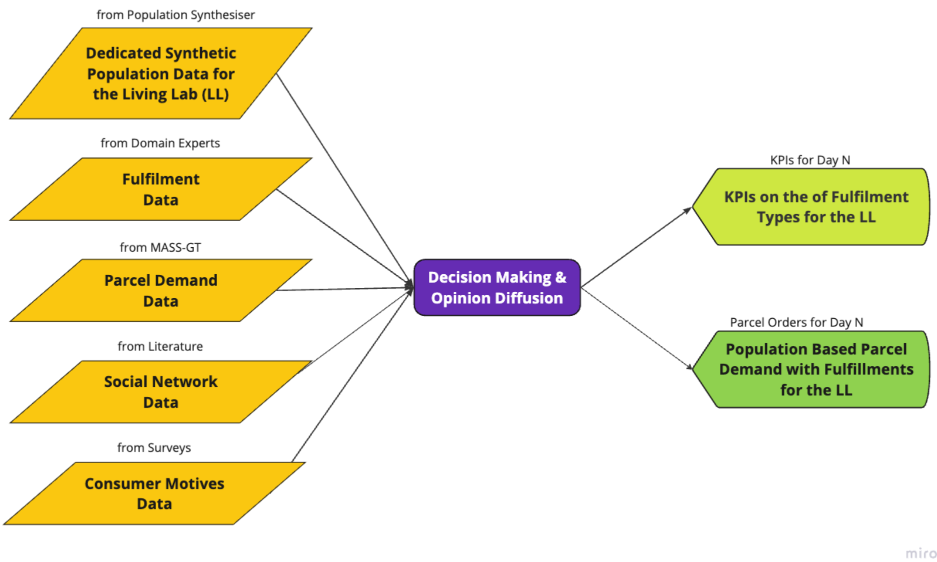

FIGURE 3 FUNCTIONAL ARCHITECTURE OF HUMAT MODULES

Initially, the module generates a population of humat agents. Each agent is equipped with sociodemographic parameters, distinct internal motives and mechanisms for evaluating choices. Following the creation of humats, the module constructs three distinct types of homophily networks in which the agents communicate with other agents: friendship, colleagues, and neighbourhood networks. In the second step of the setup, the *Decision Making & Opinion Diffusion* module, depicted in Figure 3, processes two inputs: (1) the artificial HUMAT society and (2) domain specific information related to the behavioural choices of a case study. Using these inputs, the module orchestrates the dynamic decision-making processes of the humat agents. Each agent assesses the available fulfilment types based on their internal satisfaction with each option and decides which type it prefers to choose for the next parcel order.

In every simulation step, which represents a day, the *Decision Making & Opinion Diffusion* module is activated. During each of these daily cycles, the model processes the current day's parcel demand. It then updates the satisfaction levels for each fulfilment type of each humat agent (Figure 3A), and agents take a decision about the preferred fulfilment type for parcel orders.

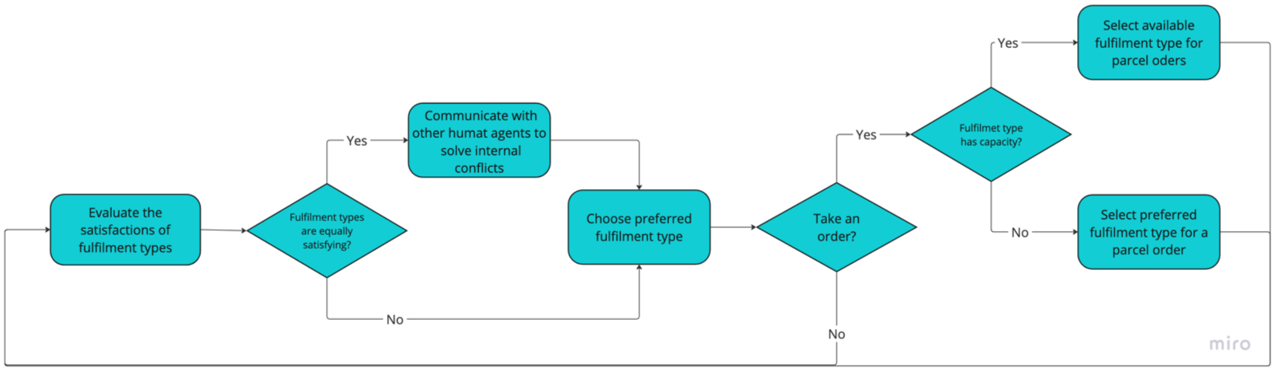

FIGURE 4 A HIGH-LEVEL ACTIVITY DIAGRAM OF HUMAT AGENTS

If a humat agent takes an order and the preferred fulfilment type is available in the home zone of that agent, the agents select the preferred fulfilment type for its next parcel order. If the preferred option has no available capacity (e.g. all parcel lockers are full), an agent selects the traditional delivery type for its next parcel order. Following these updates, the HUMAT model generates (1) an output file (inter module data) that contains the day's parcel demand with selected fulfilment types, and (2) Key Performance Indicators (KPIs) to provide a summary about the current satisfaction level of each agent with all available fulfilment types.

4.3. MASS-GT

Overview

The Multi-Agent Simulation System for Goods Transport (MASS-GT), is an agent-based model specifically, focusing on freight transport (de Bok & Tavasszy, 2018). There are various agents, including producing firms, consuming firms, shippers, own account carriers, third-party logistics (carriers), and policy makers. Figure 5 presents the overall framework of MASS-GT.

The MASS-GT framework consists of three primary modules: a shipment synthesiser, a tour formation model, and a network model (de Bok, Tavasszy, & Thoen, 2022). Within the shipment synthesiser module, two distinct components operate: one is responsible for generating the demand for parcels, and the other determines the allocation of these parcels to vehicles while organising optimal delivery routes. The tour planning component of the model processes these parcels, optimising the delivery process by establishing efficient delivery tours. Collectively, this integrated system facilitates the quantitative assessment of the impact associated with the utilisation of freight transport in conventional delivery scenarios.

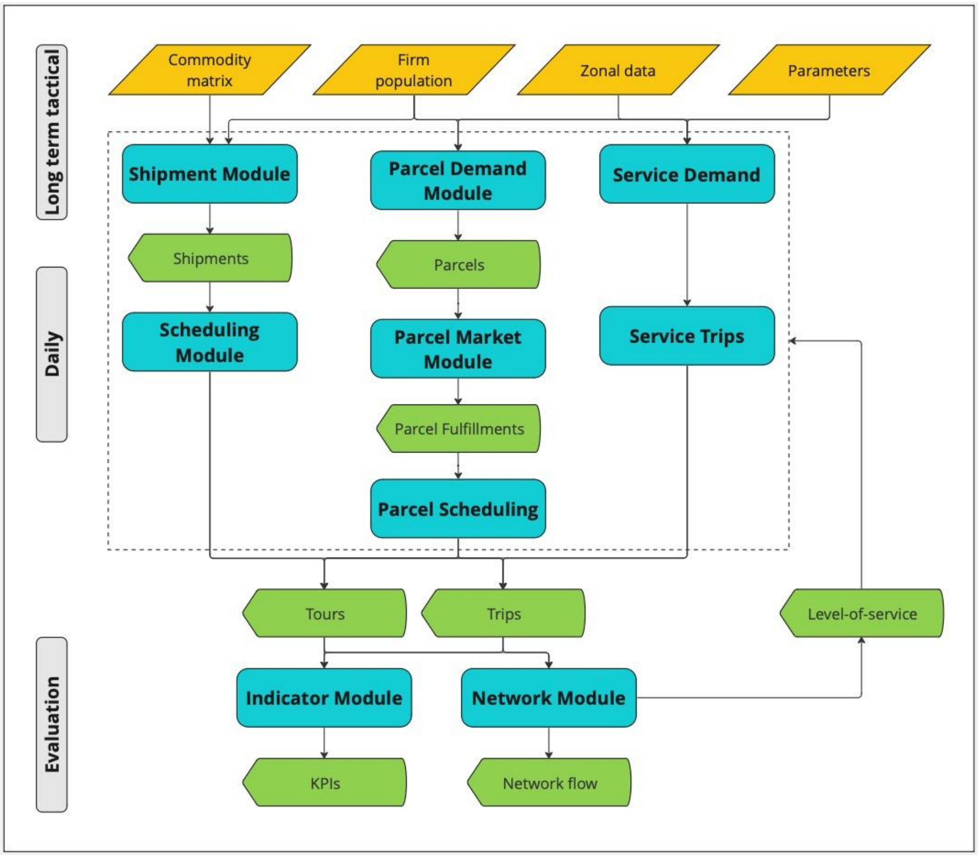

FIGURE 5 GENERAL FRAMEWORK OF MASS-GT

More specifically, MASS-GT models urban commercial vehicle movements in three segments: (1) freight shipments, (2) parcels, and (3) services (de Bok., Nadi, Tavasszy, Thoen, & Eggers, 2022). Freight shipments are considered based on the supplier probability of a firm belonging to several sectors, such as agriculture, forestry, and the construction industry. The supplier of a shipment in the logistics segment depends on the firm size and the estimated probability for that sector. This element of MASS-GT is not directly used in URBANE, as parcels are simulated separately. Additionally, parcel deliveries follow different transport patterns compared to other types of good's flows.

For the simulation of parcels, publicly available data such as networks, households, employment types, and the size of B2C and B2B parcel markets are used. The demand and delivery patterns of parcels in the use case areas are simulated using three modules: (1) The Parcel Demand module, (2) Parcel Market, and (3) Parcel Scheduling modules (de Bok. et al., 2022; Tapia, Kourounioti, Politaki, & Kakouris, 2022). These are employed in the URBANE project and are further elaborated in the following section. Lastly, the service trip module simulates light-commercial vehicle (LCV) trips for the services and construction segments.

Architecture

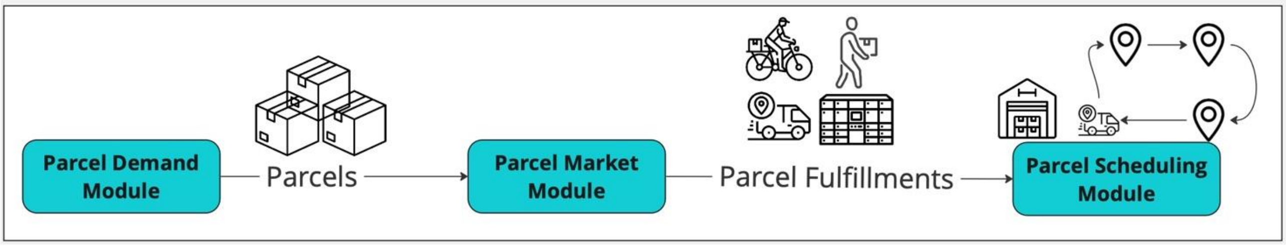

FIGURE 6 CONCEPTUAL MODEL OF MASS-GT MODULES

Since in the URBANE project, the objective of MASS-GT is to simulate the Parcel Market comprehensively, mainly three modules of MASS-GT are implemented: (1) Parcel Demand, (2) Parcel Market and (3) Parcel Scheduling (illustrated in Figure 6).

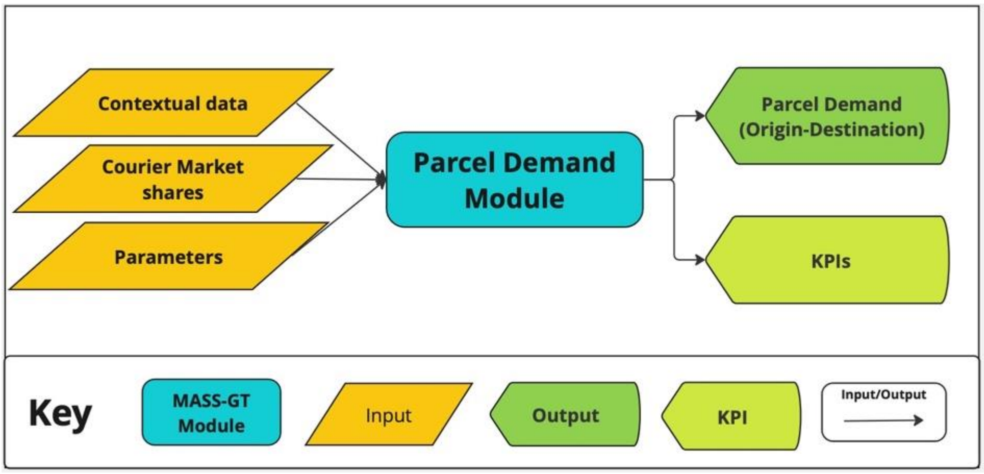

FIGURE 7 PARCEL DEMAND MODULE

The Parcel Demand module generates demand from population indicators and aggregated statistics (ACM, 2017). As illustrated in Figure 7, this module utilises contextual data, including skim matrices, network structure and sociodemographic information. Demand is generated by sociodemographic, household data and several demand parameters such as number of parcels delivered in the whole network and number of households in the network. Subsequently, the simulated parcels are allocated to specific carriers based on courier market shares and, dependent on data availability, the average delivery success rate and parcels per employment type. Consequently, this module produces the total number of parcels that carriers in the network will fulfil, along with associated KPIs.

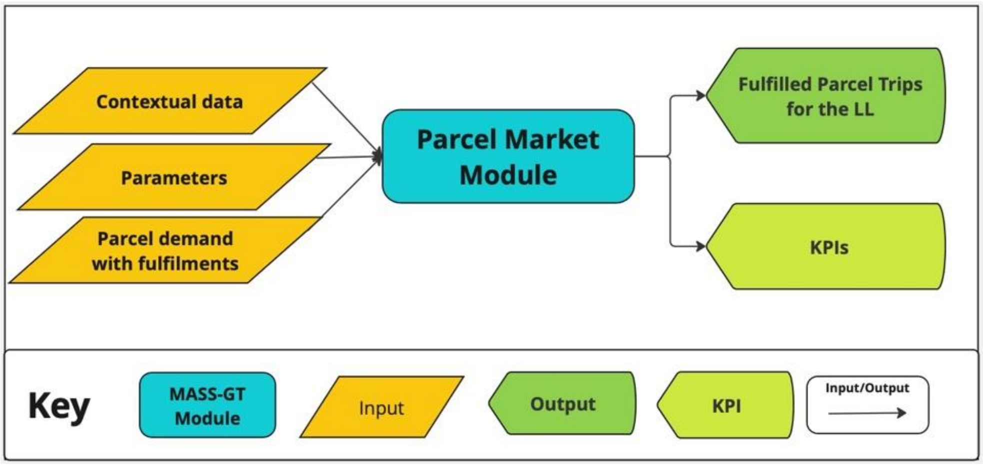

FIGURE 8 PARCEL MARKET MODULE

The Parcel Market module simulates the parcel fulfilments with assigned carriers and generates the trips to their destination. The delivery method could be a PL facility, a crowdshipping platform, or a traditional courier company. Based on the delivery method, this module generates dedicated indicators such as extra trips generated by a crowdshipper or capacity related indicators for a PL.

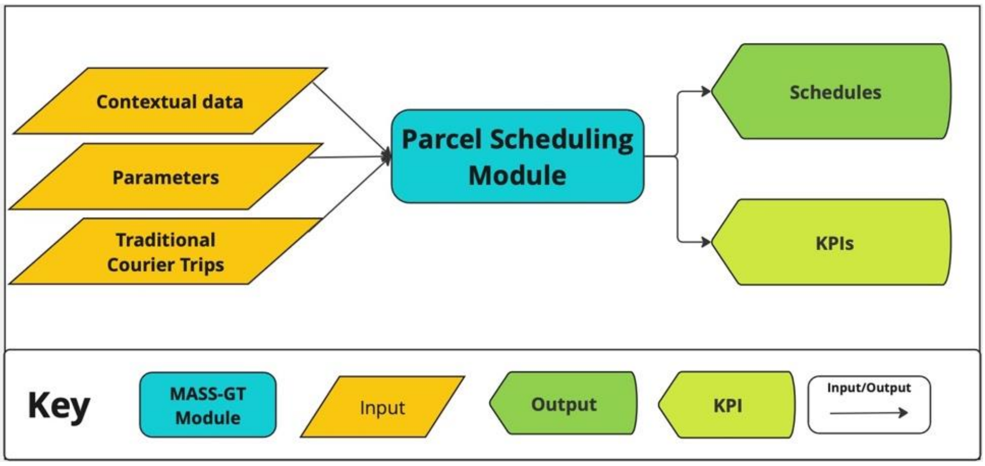

FIGURE 9 PARCEL SCHEDULING MODULE

The Parcel Scheduling module considers the parcels which are not fulfilled in the Parcel Market module as the remaining parcels are fulfilled by a traditional courier company. With the Parcel Scheduling module, the tours of a carrier are generated, and the tour distances are calculated.

4.4. VRP Module

Overview

This module addresses the Vehicle Routing Problem with Time Windows (VRPTW), aiming to find the optimal path for a delivery robot to distribute goods to various customers within specific time frames, thereby reducing the total distance travelled. The approach is a simplified version of the one utilised by the LMAD team.

The VRPTW has been extensively studied in scientific literature involving a single depot where all vehicles originate and must return after serving customers (Kallehauge, 2008). The optimisation model is defined by a fleet of homogeneous vehicles, a set of customers denoted, and a directed graph (El-Sherbeny, 2010). This graph comprises of vertices, where customers are labeled 1, 2, ... , n, and the depot is represented by vertices 0 (the starting depot) and n + 1 (the returning depot) (El-Sherbeny, 2010). In the VRPTW, there are multiple objectives. The aim is to minimise not only the number of vehicles needed but also the total travel time, waiting time, and overall travel distance incurred by the fleet of vehicles (El-Sherbeny, 2010; Kallehauge, 2008). In our current scenario, there is only one ADV, so the objective is to route the ADV optimally through all delivery points during the specified time windows. The model is easily extensible to cases where there is more than one ADV.

The VRP module processes input files detailing the robot's routes, including time, link names, and distances, alongside delivery node information such as names, types, IDs, and geographical coordinates. Additionally, it considers problem instances specifying service time windows and node waiting times. As the ADV is an electric vehicle, the VRP computes the emissions generated during its routing by considering all the sources of energy generation in the city of operation (Helsinki in this case), as the emission factors associated with each source of energy generation. The model's inputs include each delivery node's ID, the time windows during which the delivery nodes should be visited, and the time the robot waits to perform its deliveries at each node. These inputs can be varied to study a wide range of scenarios.

The outputs highlight the robot's arrival times at each destination and the chosen route, providing a comprehensive solution to efficiently manage deliveries within designated time windows.

Architecture

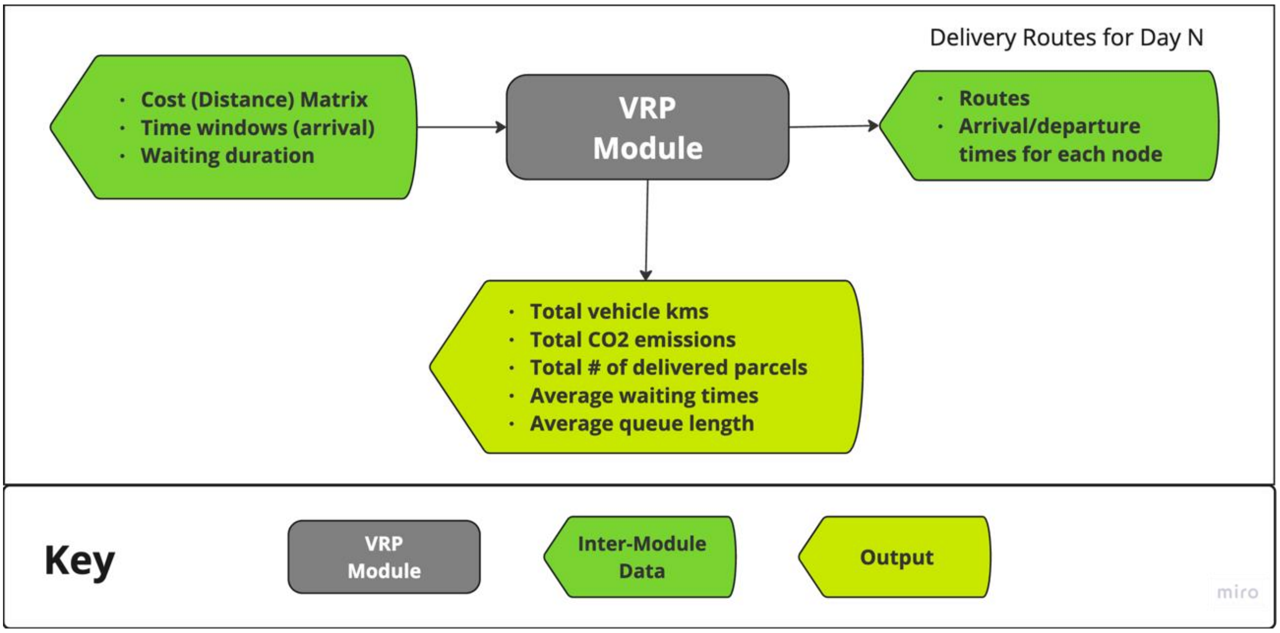

FIGURE 10 THE FUNCTIONAL ARCHITECTURE FOR THE VRP MODULE

The functional architecture of the VRP module is given in Figure 10. Here's a breakdown of the components and their relationships:

1. Input **to VRP Module:**

   a. **Cost (Distance) Matrix:** Represents the distances or costs between various delivery points, essential for calculating the optimal routes.
   b. **Time Windows (Arrival):** Specifies the acceptable arrival times at each delivery point, ensuring that deliveries are made within the required time frame.
   c. **Waiting Duration:** Indicates the expected waiting time at each delivery point, possibly due to loading/unloading or other operational delays.
2. **VRP Module:** This central component processes the inputs to generate optimized delivery routes. The VRP module uses algorithms to minimize the total travel distance, time, or other costs while adhering to the constraints like time windows and waiting durations.
3. **Inter-Module Data:**
   a. **Delivery Routes for Day N:**
      i. **Routes:** The planned paths for each vehicle for a specific day, detailing which delivery points to visit.
      ii. **Arrival/Departure Times for Each Node:** Specific times for arrival and departure at each delivery point, ensuring that the schedule aligns with the time windows and operational constraints.
4. **Output:**
   a. **Total Vehicle Kms:** The total distance travelled by all vehicles, used to assess efficiency.
   b. **Total CO_2 Emissions:** The environmental impact measured in terms of carbon dioxide emissions, indicating the sustainability of the operations.
   c. **Total Number of Delivered Parcels:** The count of parcels successfully delivered, a measure of service efficiency.
   d. **Average Waiting Times:** The average time vehicles spend waiting, reflecting operational bottlenecks or inefficiencies.
   e. **Average Queue Length:** The average number of vehicles waiting at any point, indicating congestion or scheduling issues.

5 Modelling Framework: Integration of HUMAT and MASS-GT

The aim of this section is to present the integrated agent-based modelling framework which is dedicated to modelling how consumers decide and how their decisions evolve in their social environment considering various delivery options in a LMD system.

5.1. Analyses of the Modelling Framework

Based on the descriptions given in Section 2, we identified five different types of agents (see Figure 10): consumer agents, retailer agents, supplier agents, carrier agents and public authority agents.

Consumer agents are autonomous entities that represent individual consumers in an LMD system. They place orders for parcels from retailer agents. While placing an order, consumer agents choose a delivery method from among the proposed delivery options, such as home delivery, parcel lockers, or local pickup points, and they can provide feedback on their delivery experience, influencing future choices.

Supplier agents supply products to retailer agents. Retailer agents store the supplied products and present a catalogue of them to consumer agents. They store the supplied products in their warehouses or retail locations, managing inventory levels to meet consumer demand.

Carrier agents are logistics entities that handle the physical transportation of parcels from retailer agents to consumer agents. They arrange and plan deliveries by optimizing routes, allocating resources (such as vehicles and personnel), and managing the scheduling of deliveries.

FIGURE 11 AGENT TYPES FOR LAST-MILE DELIVERY SYSTEMS

Consumer agents can be modelled as humat agents in HUMAT. This requires defining their socio-demographic characteristics, their experiential, axiological and social needs, as well as their communication networks. While consumer agents and their choices can comprehensively be modelled in HUMAT as humat agents, carrier agents and their choices can be modelled in MASS-GT's Parcel Market and Parcel Scheduling modules. Concerning, retailer agents and their decisions, publicly available data is utilised to generate demand in an aggregated fashion for the use cases.

Supplier agents cannot be directly included in the modelling framework. While the simulation of freight shipments, including the supplier of a shipment belonging to a logistics segment, is considered in the freight shipments segment of MASS-GT, this element is not directly used in the context of URBANE. This is because the simulation of parcels is inherently different and modelled under MASS-GT's parcels segment separately.

Lastly, public authority agents are included in our modelling framework. Although the public authority plays a critical role in the last-mile, i.e. directly influencing carrier decisions such as vehicle types, curbside usage, and zero-emissions zones, its influence on how consumers choose a delivery option is limited.

5.2. Design of the Modelling Framework

In this section, we describe the architectural design of our integrated high-level modelling framework for LMD systems (Gürcan et al., to appear) as a functional architecture[5]. The modelling framework identifies the interconnections and complementarities between HUMAT and MASS-GT and develops a logical structure between them that can ensure the transferability of the models for future digital social twinning applications. It is designed with modularity, standardized interfaces, and clear documentation, making it easily be adopted for simulating the uptake of social innovation studies in various Wave 1 LLs in selected, relevant contexts (see Section 6). Due to the same properties, the adopted Wave 1 models are easily replicable for Wave 2 LLs.

The functional architecture consists of two main elements: (1) Setup and (2) Execution that are shown in Figure 12.

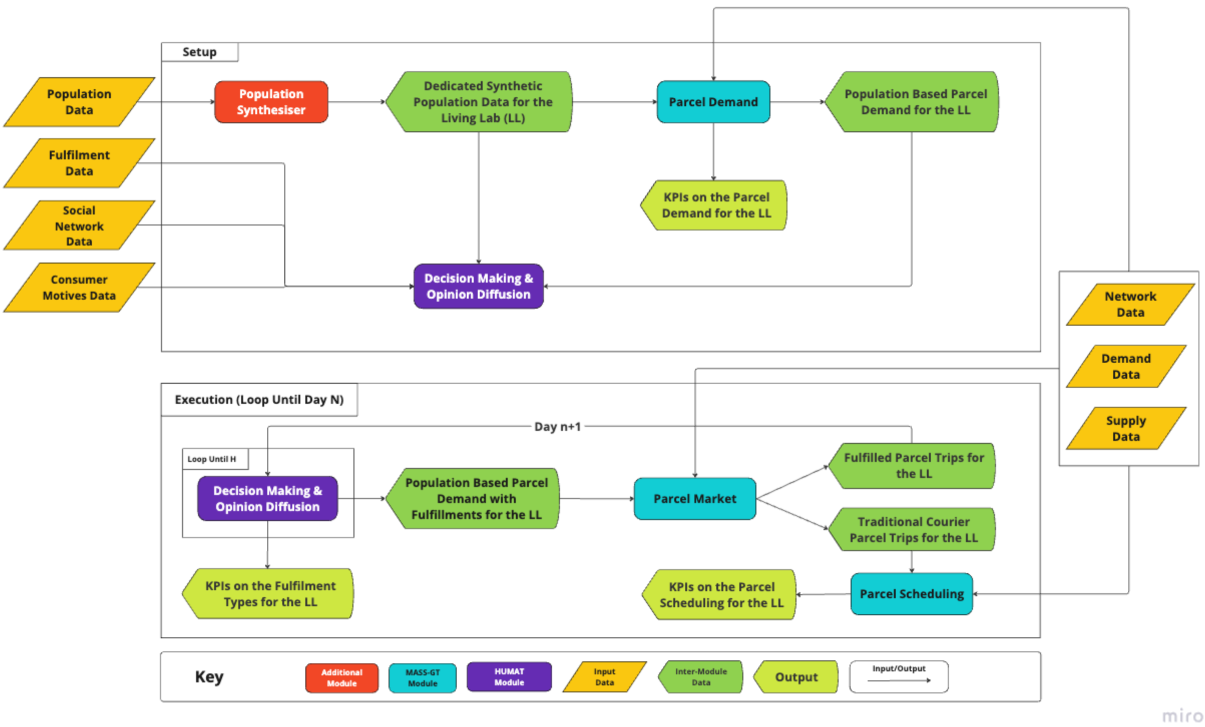

FIGURE 12 INTEGRATED HIGH-LEVEL MODELLING FRAMEWORK

In the Setup phase, the population synthesiser uses the population data to generate a synthetic population for the LLs (see details in Annex III: EU-SILC Data). After generating the dedicated synthetic population, MASS-GT's Parcel Demand module generates household level parcel demand and corresponding KPIs. Zonal level parcel demand generation is implemented with the use of household data generated by the population synthesiser. The connection between zonal data of MASS-GT is established by linking it with households based on the number of households in the network. Detailed explanations for this process can be found in Section 7 for each LL application.

Subsequently, HUMAT's Social Network & Motives generator module institutes an artificial society of heterogeneous interconnected humat agents. Each humat is generated based on individual

[5] A functional architecture is an architectural model from a usage perspective which is composed of the modules (blocks) that represent each software entities and flows that represent the interactions between these entities.

sociodemographic datapoints, provided by the population synthesiser, and combined with a set of motives provided by survey data or ad hoc assumptions (where empirical data is not available).

Finally, HUMAT's Decision Making & Opinion Diffusion module uses the output of previously described modules (Population Based Parcel Demand for the LL and Artificial HUMAT Society for the LL) and initiates the model dynamics (communication in social networks and evaluation of choice alternatives) to get an initial calibration for behavioural preferences in the artificial population of a LL.

In the Execution phase, MASS-GT's Parcel Market module assigns fulfilled parcel trips with their respective origins and destinations. Depending on the innovation being tested, this module generates KPIs related to the delivery service. Subsequently, traditional courier parcels are transferred to the Parcel Scheduling module, where delivery tours are generated for each courier. This module provides the number of tours as well as the total vehicle kilometres driven to derive CO_2 emissions.

HUMAT's Decision Making & Opinion Diffusion module has two main functions. It calculates which services an agent is using when ordering a parcel, and it provides agents with capabilities to communicate with other agents about the available delivery choices. Finally, the module generates KPIs related to the satisfaction of individuals in the artificial society of a LL with available fulfilment types.

5.3. Data of the Modelling Framework

Input Data

Population Data: Population information in the simulation covers the sociodemographic characteristics (including age, gender, and income) of the population of the use case country. For this purpose, we adopt micro data provided by Eurostat – European statistics on income and living conditions (EU-SILC). This data source is the base for further processing in population synthesizer and enriched with the use of information received from the LL (including zoning, households, and population size). In the final step, we add a unique identifier for each synthetic humat agent, connecting each socio-demographic segment to information about motives from survey data.

Consumer Motives Data: provides information on the importances of experiential, social and axiological motives and satisfactions about LL-specific LMD choices. For this purpose, surveys (refer to Deliverable 2.1 Validation report of Lighthouse LLs Implementation) were conducted in use case LLs.

Network Data: These data include several essential inputs to create the zoning of the network. External zones and depot locations are classified in this category. Additionally, zonal skim matrixes such as time and distance are considered in this category. These data were received from the Thessaloniki LL.

Demand Data: These data include sociodemographic characteristics and household data to generate household demand for the network. These data were received from the Thessaloniki LL.

Supply Data: These data include the supply characteristics of the network such as courier market shares and courier network. These data were received from the Thessaloniki LL.

Inter-Module Data

These are transmitted between various modules to enable interoperability and coordinated functionality.

Output Data

KPIs on the Parcel Demand for the LL (available for every day of the simulation, for each city zone)

- Total demand – the number of parcels delivered
- Demand per courier – the number parcels delivered per courier company

KPIs on the Fulfilment Types for the LL (available for every day of the simulation, for each city zone)

- Demand per fulfilment type – the number of parcels preferred to be delivered via fulfilment type
- Usage per fulfilment type – the number of parcels delivered via fulfilment type
- Available capacity per fulfilment type

KPIs on the Parcel Scheduling for the LL (available for every day of the simulation)

- Direct KPIs:
  - Total vehicle kilometres
  - Total vehicle kilometres per courier company
  - Total number of tours
  - Number of parcels (traditional)
  - Number of parcels (PL)
- Efficiency KPIs:
  - Distance per tour (total/vkm)
  - Distance per parcel(total/vkm)
  - PL parcel per tour (total)

5.4. Implementation of the Modelling Framework

HUMAT and MASS-GT modules are implemented as independent Python projects. To implement the modelling framework, they are deployed as Python modules (MASS-GT module and HUMAT module) and are integrated in dedicated use cases for the LLs. Below, we outline the steps to set up the framework locally with bash (windows) or terminal (mac). The example is given on the HUMAT module, please keep in mind that the process needs to be repeated for MASS-GT, descriptions and code examples are given in the **README.rd** file in the project files.

Install the modules locally

To ensure the functionality of the modules, the modules are first installed locally in editable mode:

pip install -e . . The -e flag denotes editable, while the . specifies the current directory. This command establishes a link from your project directory to the Python site-packages directory, facilitating testing without the need for frequent reinstallation after each modification.

Build the module

Employ setuptools to build the module ***python setup.py sdist bdist_wheel*** . This command generates both a source distribution and a wheel distribution of the module within the dist/ directory.

The **setup.py** file is a script used in Python packaging to describe the metadata of the Python project. It typically contains information such as the project name, version, author, description, dependencies, and instructions for installation.

```
setup(
    name='HUMAT',
    version=get_version(),
    description='HUMAT Python API',
    author='Timo Szczepanska, Önder Gürcan',
    author_email='timo@norceresearch.no',
    long_description=long_description,
    long_description_content_type='text/markdown',
    url='https://gitlab.com/urbane-horizon-europe/model-library/humat',
    keywords='urbane, python, model, humat',
    package_dir={'': 'src'},
    packages=find_packages(where='src'),
    python_requires='>=3.8, <4',
    install_requires=[
        'pandas',
        'python-dotenv'
    ],
    entry_points={
        'console_scripts': [
            'pymodel=humat.__main__:main'
        ],
    },
    project_urls={
        'Bug Reports': 'https://gitlab.com/urbane-horizon-europe/model-library/humat/issues',
        'Source': 'https://gitlab.com/urbane-horizon-europe/model-library/humat',
    }
)
```

FIGURE 13 SETUP CONFIGURATION FOR BUILDING THE PYTHON MODULE

Install the module locally

Install the module locally “pip install dist/HUMAT-1.0.0-py3-none-any.whl”. If necessary, you can uninstall your module, with “pip uninstall humat” .

Using the module in a project

Once a module is established locally, it can integrate into other Living Lab applications. The following demonstrates how to instantiate it.

```
from humat.HumatModel import HumatModel
self.decision_making = HumatModel(params)
```

The implementation of the HUMAT and MASS-GT models has already been uploaded/committed to the Gitlab repository[6] of the URBANE platform (see Figure 14). They are under the Task 3.4 group of the Model Library group.

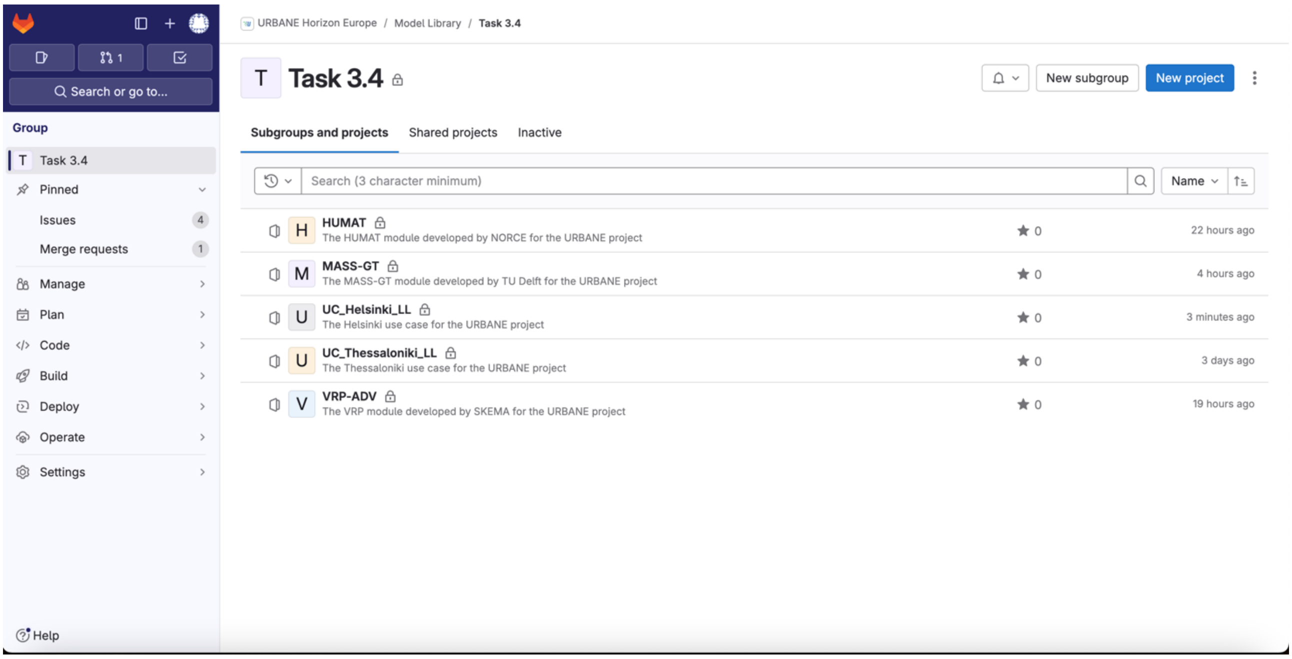

FIGURE 14 THE URBANE PLATFORM GITLAB REPOSITORY - TASK 3.4

[6] https://gitlab.com/urbane-horizon-europe/model-library/Task3.4, last access on 7 August 2024.

6 Case Studies: Agent-based Models for Living Labs

In this section, we provide detailed explanations of the use cases used for testing and calibrating our agent-based modelling framework. These use cases include PL facility (Section 6.1) and autonomous delivery vehicle (ADVs) service (Section 6.2). While former is modelled using HUMAT and MASS-GT, latter is modelled using a combination of HUMAT, MASS-GT, and VRP models since MASS-GT modules are not capable of simulating the behaviour of the ADVs.

6.1. Parcel Locker Service (Thessaloniki LL)

6.1.1 System Overview and Motivations

Thessaloniki LL is Greece's second-largest city. The city centre experiences a dense population and a scarcity of public spaces. Due to the increasing commercial activities that contribute to high levels of passenger traffic and urban freight movements, Thessaloniki LL aims to propose PL facilities in the city for LMDs.

To explore the acceptability of PL facilities, the modelling framework given in Section 5 can be calibrated and used for such a use case. In this use case, while the HUMAT modules simulate consumer choices between the PL facility and home delivery options over time, the allocation of carrier trips is simulated by the MASS-GT modules. To achieve this, the capacity of a PL is considered for each zone. The remaining parcels which cannot be delivered to a PL due to the capacity constraints are transferred to carriers in the network as these need to be delivered to consumers' address by traditional delivery.

In Figure 15, we provide a map showing Thessaloniki and its zones.

FIGURE 15 THE ZONES OF THESSALONIKI

Several motivations behind the choice of the Thessaloniki LL are as follows:

- The LL aims to explore the Physical Internet (PI) green last-mile logistics and assess willingness to accept services, particularly PLs.

- Based on the objectives of the Thessaloniki LL aims to evaluate the impact of PLs, including factors like demand variations under different scenarios.
- The agent-based model facilitates the estimation of the uptake of PLs, providing valuable insights into potential adoption rates.

6.1.2 Data Preparation for the Parcel Locker Service

Preparation of MASS-GT Data[7]

The MASS-GT simulator requires diverse input data to model LMD systems effectively. These data are categorised into network, supply, and demand sub-sections, each with specific roles in the simulation process. Table 3 below outlines the input data and the respective modules they are used in MASS-GT.

TABLE 3 MASS-GT DATA FOR THESSALONIKI LL

Data name	File type	Description	Used by
Network Data			
Zones	Shape file	Centroids representing the zonal network of the study area	Parcel demand, Parcel market, Parcel scheduling
External zones*	Shape file	Zones which are outside of the study area	Parcel demand, Parcel market, Parcel scheduling
Parcel nodes	Shape file	Point vector showing the depot locations of the courier companies in the network	Parcel demand, Parcel market, Parcel scheduling
Duration matrix	.csv text	Duration matrix (in seconds) between each combination of the zone	Parcel demand, Parcel market, Parcel scheduling
Distance matrix	.csv text	Distance matrix (in metres) between each combination of the zone	Parcel demand, Parcel market, Parcel scheduling
Supply Data			
Locker network	.csv text	Locations of the lockers in the network	Parcel market
Departure times of parcels	.csv text	Cumulative probability distribution of departure times (one full day) for the parcel tours	Parcel scheduling
Demand Data			
Sociodemographic characteristics	.csv text	Population characteristics in the study area	Parcel demand
Courier market shares	.csv text	Market shares of the courier companies in the network	Parcel demand

[7] A detailed representation of how the data is processed can be found in Annex I: Input Data Preparation for MASS-GT for Thessaloniki LL.

Network data

Zones: Represent the centroids of different zones within the study area, serving as the fundamental units for modelling and analysis in parcel demand, market, and scheduling modules.

External zones: Represent zones outside the study area, considered in the parcel demand, market, and scheduling modules to account for external influences on the delivery network.

Parcel nodes: Identify the locations of courier company depots within the network, essential for determining starting points for parcel deliveries in demand, market, and scheduling modules.

Duration matrix: A matrix that provides the travel time in seconds between each pair of zones, crucial for determining travel times in demand generation, market analysis, and scheduling.

Distance matrix: Like the duration matrix but provides the distance in metres between each pair of zones, used for the same purposes as the duration matrix.

Supply data

Locker network: Indicates the positions of lockers available in the network, used primarily in the parcel market module to analyse delivery locker network.

Departure times of parcels: Represent the cumulative probability distribution of parcel departure times throughout a day, used in the parcel scheduling module to simulate the timing of parcel dispatches.

Demand data

Sociodemographic characteristics: Provide information on the population characteristics within the study area, which is used to generate parcel demand based on population distribution and behaviours. These include sociodemographic characteristics of the population such as income and household structure such as number of households and people in the study area.

Courier market shares: Show the market share distribution among different courier companies, impacting the demand module by determining how parcels are allocated among various couriers.

Preparation of HUMAT Data

HUMAT also requires diverse input data to model consumer behaviour effectively. These data are categorised into synthetic population, fulfilment, social network and consumer motives sub-sections, each with specific roles in the simulation process. Table 4 below outlines the input data and the respective modules they are used in HUMAT.

TABLE 4 HUMAT DATA FOR THE THESSALONIKI LL

Category	Dataset name	File type	Description	Used by
Synthetic Population Data	SyntheticPopulation	.csv	A list of agents with parameters representing the population of the Thessaloniki LL.	Decision Making & Opinion Diffusion
Fulfilment Data	LockerNetwork	.csv	Locations of the lockers in the network, types of lockers, owner companies and capacity.	
Social Network Data	SocialNetwork	.json	A dictionary containing calibration data about networks.	

Consumer Motives Data	Motives	.json	A dictionary containing calibration data about consumer motive importances.	
	Choices	.json	A dictionary containing calibration data about agent choice satisfactions.	

Synthetic Population Data

Wasserstein Generative Adversarial Networks, a neural network architecture that can make realistic and varied copies of original data, creates synthetic populations for the agent-based models. EU-SILC cross-sectional living condition data train these models. Researchers can obtain EU-SILC data through Eurostat or local agencies that distribute official data sets. Many personal and household data linked to the individual level are available across all EU countries and collaborative nations outside the EU. The method for generating synthetic populations is described in "Annex III: EU-SILC Data", along with an overview of the dataset and variables used. The final synthetic populations are the full-scale adult population of the Thessaloniki and Helsinki municipalities.

Fulfilment Data

The fulfilment data ("LockerNetwork.csv") contains detailed information about the PL network in Thessaloniki (Table 5). The baseline setting data, provided by the project partners from the Thessaloniki LL, is used as an input in all simulation scenarios. Each row of the file provides information about a single parcel locker. Each locker is characterized by an owner company ("Cep"), location coordinates ("Lat/Lon"), a zone id ("Areanr"), a parcel capacity ("Capacity"), a status ("Status_type").

TABLE 5 STRUCTURE OF THE FULFILMENT DATA INPUT.

Variable	Description	Type	Values
Cep	Contains the company that owns the locker	string	"Company 1", "Company 4", "Company 7"
Lat	Spatial latitude of the PL	float	(decimal degrees)
Lon	Spatial longitude of the PL	float	(decimal degrees)
Areanr	Id of the zone the locker is located	integer	Range between 1 and 120
Status_type	Describes if the locker can be used only by the owning company or by all companies	string	"private", "public"

Social Network Data

Social network data contains information to configure social networks in which humat agents communicate with other humat agents. The social network data is arranged in the form of a dictionary and saved in ".json" format ("SocialNetworks.json"). The overall social networks, in which all humat agents are embedded, is a summary of all the social network types for each humat. Each social network is categorized by type ("network_type"), average number of links ("n_links"), relevant homophily dimensions and corresponding homophily strengths ("attributes").

TABLE 6 SOCIAL NETWORKS OF HUMAT AGENTS

Network type (string)	Average number of links (integer)	Homophily dimensions (categorical)	Homophily strength (integer)
Friendship	4	age group	90 (high)
		sex	30 (low)
		education	30 (low)
Colleagues	2	education	90 (high)
		occupation	90 (high)
Neighbours	2	living location	90 (high)
		age group	30 (low)

In the current Thessaloniki URBANE ABM configuration, the social network data includes three network types: friendship, colleagues, and neighbours (see Table 6). During a simulation, each of these networks is created based on homophiles, represented by proximity between the agent parameters: sex (M, F), age group (18-39, 40-64, 65+), education level (not higher education, higher education), occupation (1-9), and living location (zone level). The strength of the homophily in one category can be strong (90% similar, 10% random), medium (60% similar, 40% random), or weak (30% similar, 70% random). A strong connection means there is a 90% chance that a link is formed between agents with the same categorical values in a socio-demographic parameter; a medium strength means there is a 60% chance, and a weak strength means there is a 30% chance.

In the friendship network each humat has on average 4 links, with 90% of the linked agents being in the same age group, 30% in the same sex category, and 30% in the same education category. In the colleague network, each humat has on average, 2 links, with 90% of the linked agents sharing the same education level and 90% the same occupation. In the neighbours' network, there are 2 links, with 90% of the linked agents living in the same living location and 30% in the same age group.

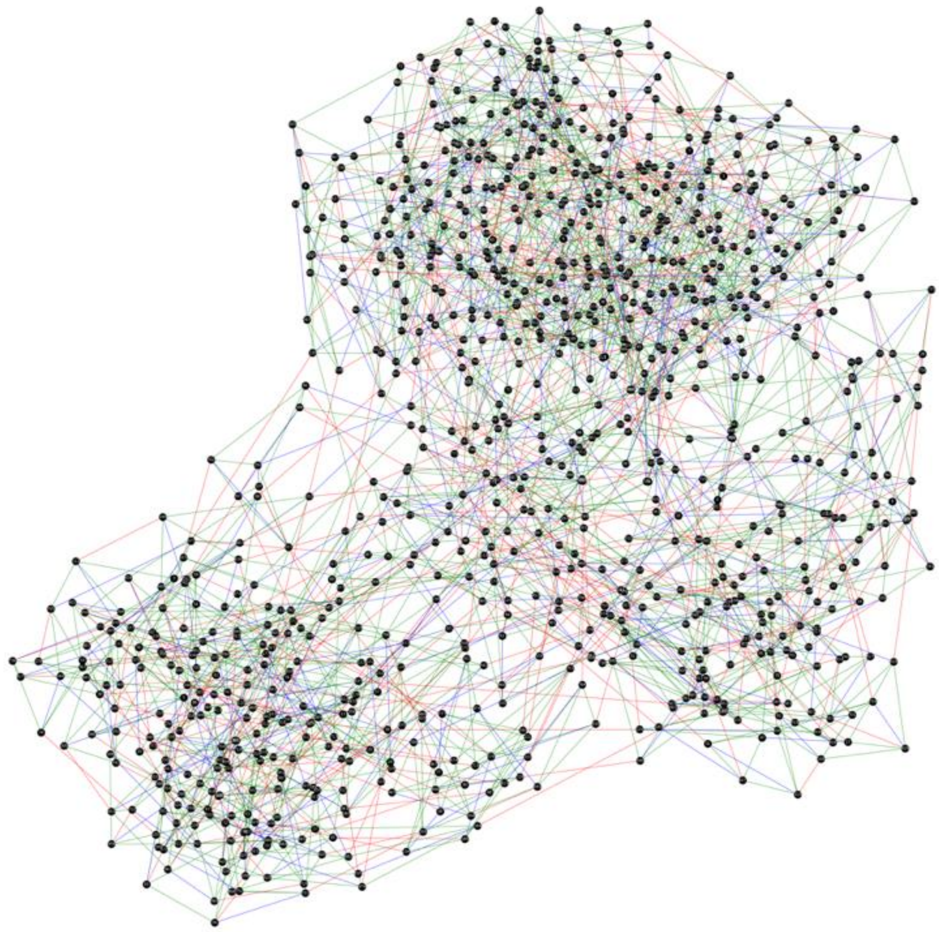

FIGURE 16 EXAMPLE OF A SOCIAL NETWORK CONTAINING LINKS FOR FRIENDSHIPS, COLLEAGUES AND NEIGHBOURS

Figure 16 illustrates a social network containing links for friendships, colleagues and neighbours for N= 1000 humat agents. Colleagues network links are denoted as red, while neighbours as blue, and friends as green.

Consumer Motives Data

Consumer Motives Data were used in simulation scenarios and are described in section 7.1, (see Parameter 5. Consumer satisfactions). In both simulation scenarios, the motive and fulfilment type satisfaction for four socio-demographic segments (where empirical data was available) were partially informed by the data from the Thessaloniki URBANE survey. The Thessaloniki URBANE survey was launched in February 2024 on the EUSurvey service[8]. The data used to calibrate the URBANE ABM was collected until the 15th of May.

The raw dataset comprises of 188 responses, which were divided into the socio-demographic segments defined by a combination of sex (M, F), age group (18-39, 40-64, 65+), education level (not higher education, higher education) and employment status (not employed, employed). Table 7 shows the frequency of respondents belonging to each socio-demographic segment.

[8] EUSurvey service, https://ec.europa.eu/eusurvey/runner/LOCKERSURVEY, last access on 9 August 2024.

TABLE 7 SOCIO-DEMOGRAPHIC SEGMENT SHARES IN THE THESSALONIKI URBANE SURVEY.

Socio-demographic segment	Frequency	Percent
M, 18-39, NOT HIGHER, NOT EMPLOYED	1	0,5
M, 18-39, HIGHER, EMPLOYED	50	26,6
M, 39-64, NOT HIGHER, EMPLOYED	2	1,1
M, 39-64, HIGHER, NOT EMPLOYED	1	0,5
M, 39-64, HIGHER, EMPLOYED	44	23,4
M, 65+, HIGHER, NOT EMPLOYED	3	1,6
M, 65+, HIGHER, EMPLOYED	2	1,1
F, 18-39, NOT HIGHER, NOT EMPLOYED	1	0,5
F, 18-39, HIGHER, NOT EMPLOYED	1	0,5
F, 18-39, HIGHER, EMPLOYED	46	24,5
F, 39-64, HIGHER, EMPLOYED	34	18,1
F, 65+, HIGHER, NOT EMPLOYED	2	1,1
Total	187	99,5
Missing	1	
Total	**188**	**100**

Empirical data on motive importances and fulfilment type motive satisfactions for segments represented by 34 or more respondents were used to inform the Decision Making and Opinion Diffusion module of the ABM. As a result, the preferences of four segments were informed by empirical data:

- M, 18-39, HIGHER, EMPLOYED,
- M, 40-64, HIGHER, EMPLOYED,
- M, 18-39, HIGHER, EMPLOYED,
- M, 40-64, HIGHER, EMPLOYED.

Information on motive importances were collected by asking respondents *When deciding to have goods delivered home or to a parcel locker, how important are the following aspects for you*:

- *I can get the parcel at a convenient time*
- *The delivery has low environmental impact*
- *The working conditions of the courier delivering the package*
- *The delivery cost is low*
- *The parcel details are kept private (item types or the sender is not revealed)*

Respondents evaluated each aspect on the scale of 0 (*not important at all*) to 10 (*absolutely essential*).

Information on motive satisfactions for each fulfilment type (home delivery/parcel locker) were collected by asking respondents *to what degree do you consider (home deliver/parcel locker) positive or negative regarding*:

- *Receiving a parcel at a convenient time*
- *Low environmental impact*
- *Good working conditions of the courier*
- *Low delivery cost*
- *Privacy of the parcel details (item types or the sender is not revealed)*

Respondents evaluated each aspect on the scale of -5 (*very negative*) to 5 (*very positive*), with 0 (*neutral*) in the middle of the scale.

TABLE 8 FILE PARAMETERS AND DESCRIPTION FOR CONSUMER MOTIVES DATA[9].

Parameter	Description	Type	Possible values
Segment	Socio-demographic segment.	integer	(1111 –2322)
Name	Name of the motive.	string	convenient_time, working_conditions, low_environmental_impact, low_delivery_costs, working_conditions, privacy
Type	Motive type	string	values, experiential, social
a and b	Alpha and beta of a random beta-distribution	float	0-5.0

Based on the survey results the model is informed with consumer motives data (Table 8). The motive data (motives.json, choices.json) contains details about the socio-demographic segments and the corresponding motives that influence decision-making processes. The motives are characterized by a segment identifier (“segment”), a descriptive name of the motive (“name”), the type of motive (“type”), and statistical parameters (“a”, “b”) that define the alpha and beta values for a random beta distribution.

6.1.3 Calibrated and Validated ABM for the Parcel Locker Service

Calibration refers to fine-tuning software components to achieve desired output levels of the selected use case. This might involve setting parameters, fine-tuning inputs and outputs, adjusting algorithms, or optimizing configurations to meet specific criteria. This process ensures that the model accurately represents the use case being studied.

[9] “motives.json” and “choices.json”

The integrated HUMAT and MASS-GT models are conceptualised as depicted in Figure 23.

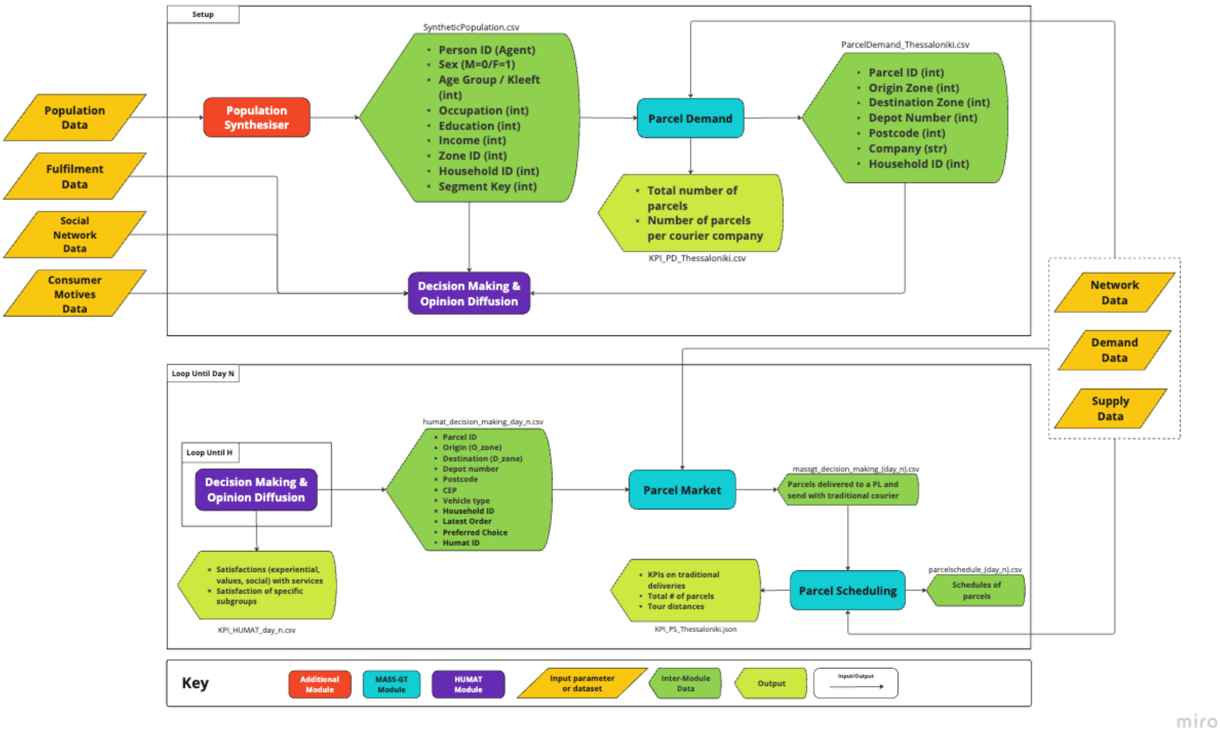

FIGURE 17 MODELLING FRAMEWORK CALIBRATED FOR THESSALONIKI LL

As detailed in Section 6, the population synthesiser generates a synthetic Thessaloniki population for input into both models, then the parcel demand is initialized and after the decision-making of consumers is initialized. The simulation runs through multiple days, with iterative decision-making and parcel market optimization (i.e. assigning parcels to PL delivery and to home delivery). Outputs are tracked in terms of satisfactions of consumers, parcel delivery efficiency and environmental impact, with continuous feedback loops to refine the model.

Synthetic Population Data

The synthetic population is comprised of 24 socio-demographic segments defined by a combination of sex (M, F), age group (18-39, 40-64, 65+), education level (not higher education, higher education) and employment status (not employed, employed). The shares of each segment are summarized in Table 9. The socio-demographic characteristics defining the segments were chosen to maximize the reliable information about consumer motives provided by the Thessaloniki URBANE survey data. Note that the age characteristic used in linking the EU-SILC and survey could not be standardized between the two data sources. Therefore, the closest age categories were linked together.

TABLE 9 SOCIO-DEMOGRAPHIC SEGMENT SHARES IN THE SYNTHETIC POPULATION OF THESSALONIKI.

Socio-demographic segment	Frequency	Percent
M, 18-39, NOT HIGHER, NOT EMPLOYED	934	3.2
M, 18-39, NOT HIGHER, EMPLOYED	518	1.8
M, 18-39, HIGHER, NOT EMPLOYED	239	0.8
M, 18-39, HIGHER, EMPLOYED	436	1.5
M, 40-64, NOT HIGHER, NOT EMPLOYED	286	1.0
M, 40-64, NOT HIGHER, EMPLOYED	1106	3.8
M, 40-64, HIGHER, NOT EMPLOYED	76	0.3
M, 40-64, HIGHER, EMPLOYED	670	2.3
M, 65+, NOT HIGHER, NOT EMPLOYED	6441	22.0
M, 65+, NOT HIGHER, EMPLOYED	1395	4.8
M, 65+, HIGHER, NOT EMPLOYED	1177	4.0
M, 65+, HIGHER, EMPLOYED	480	1.6
F, 18-39, NOT HIGHER, NOT EMPLOYED	1202	4.1
F, 18-39, NOT HIGHER, EMPLOYED	274	0.9
F, 18-39, HIGHER, NOT EMPLOYED	257	0.9
F, 18-39, HIGHER, EMPLOYED	354	1.2
F, 40-64, NOT HIGHER, NOT EMPLOYED	493	1.7
F, 40-64, NOT HIGHER, EMPLOYED	950	3.3
F, 40-64, HIGHER, NOT EMPLOYED	128	0.4
F, 40-64, HIGHER, EMPLOYED	746	2.6
F, 65+, NOT HIGHER, NOT EMPLOYED	7903	27.0
F, 65+, NOT HIGHER, EMPLOYED	1372	4.7
F, 65+, HIGHER, NOT EMPLOYED	1161	4.0
F, 65+, HIGHER, EMPLOYED	621	2.1
Total	**29219**	**100**

Fulfilment Data

Calibration used in the baseline scenarios is provided by the Thessaloniki LL. The file contains a total of 59 lockers belonging to three companies (Table 10).

TABLE 10 THE NUMBER OF PARCEL LOCKERS PER COMPANY IN THESSALONIKI LL

Company	Number of parcel lockers
Company 1	15
Company 4	3
Company 7	41

Social Network Data

Due to lack of empirical data describing the topology of social networks in Thessaloniki, the ABM was not empirically calibrated to the Thessaloniki parcel locker use case with respect to this aspect. The rules for generating social networks followed the description from Section 6.1.2.

Consumer Motives Data

In the process of calibrating the model, the data on motive importances and fulfilment type motive satisfactions were normalised to the range between 0 and 1, and subsequently means, standard deviations, skewnesses and kurtoses were calculated for the relevant socio-demographic segments. Subsequently, alpha and beta values of a beta distribution producing means and variances corresponding to the means and variances of empirical distributions were identified and used as input to generate relevant characteristics of the humat agents belonging to the target socio-demographic segments. Since theoretical values of motive satisfactions lay in the range between -1 and 1 (and not between 0 and 1), an additional min-max normalization step is implemented in the ABM.

Table 11, Table 12 and Table 13 present the characteristics of the distributions (mean, standard deviation, skewness, kurtosis) in the empirical data and the ABM, alongside the corresponding alpha and beta values of the beta distributions. It is worth noting that means and standard deviations in the empirical data and the calibrated ABM simulation are identical, however there are minor differences in the values for skewness and kurtosis. This is a limitation of small sample sizes in the empirical data.

TABLE 11 DISTRIBUTION CHARACTERISTICS OF MOTIVE IMPORTANCES IN THE EMPIRICAL DATA AND ABM FOR THE EMPIRICALLY INFORMED SOCIO-DEMOGRAPHIC SEGMENTS.

Segment label	Motive	Beta		Empirical data				ABM			
		alpha	beta	mean	variance	skewness	kurtosis	mean	variance	skewness	kurtosis
M, 18-39, HIGHER, EMPLOYED	Convenient time	2,208	0,256	0,896	0,027	-1,839	3,139	0,896	0,027	-2,163	4,638
M, 39-64, HIGHER, EMPLOYED	Convenient time	2,416	0,189	0,927	0,019	-2,282	4,689	0,927	0,019	-2,714	8,008
F, 18-39, HIGHER, EMPLOYED	Convenient time	4,228	0,504	0,894	0,017	-1,370	1,238	0,894	0,017	-1,815	3,524
F, 39-64, HIGHER, EMPLOYED	Convenient time	4,029	0,279	0,935	0,011	-2,353	7,243	0,935	0,011	-2,585	7,832
M, 18-39, HIGHER, EMPLOYED	Low environmental impact	0,672	0,615	0,522	0,109	-0,432	-1,085	0,522	0,109	-0,081	-1,392
M, 39-64, HIGHER, EMPLOYED	Low environmental impact	1,090	0,707	0,607	0,085	-0,863	-0,157	0,607	0,085	-0,385	-1,075
F, 18-39, HIGHER, EMPLOYED	Low environmental impact	1,454	0,901	0,617	0,070	-0,920	0,221	0,617	0,070	-0,406	-0,919
F, 39-64, HIGHER, EMPLOYED	Low environmental impact	1,442	0,559	0,721	0,067	-1,174	0,669	0,721	0,067	-0,852	-0,330
M, 18-39, HIGHER, EMPLOYED	Good working conditions	1,117	0,555	0,668	0,083	-0,881	0,194	0,668	0,083	-0,635	-0,809
M, 39-64, HIGHER, EMPLOYED	Good working conditions	0,948	0,734	0,564	0,092	-0,498	-0,791	0,564	0,092	-0,228	-1,220
F, 18-39, HIGHER, EMPLOYED	Good working conditions	1,026	0,526	0,661	0,088	-0,907	0,020	0,661	0,088	-0,611	-0,880
F, 39-64, HIGHER, EMPLOYED	Good working conditions	1,678	0,679	0,712	0,061	-0,604	-0,293	0,712	0,061	-0,787	-0,365
M, 18-39, HIGHER, EMPLOYED	Low delivery costs	2,090	0,340	0,860	0,035	-2,393	8,117	0,860	0,035	-1,735	2,579
M, 39-64, HIGHER, EMPLOYED	Low delivery costs	3,460	0,557	0,861	0,024	-1,297	1,198	0,861	0,024	-1,557	2,265
F, 18-39, HIGHER, EMPLOYED	Low delivery costs	2,873	0,374	0,885	0,024	-1,498	1,592	0,885	0,024	-1,894	3,557
F, 39-64, HIGHER, EMPLOYED	Low delivery costs	6,684	0,330	0,953	0,006	-1,721	2,933	0,953	0,006	-2,685	9,138
M, 18-39, HIGHER, EMPLOYED	Privacy	1,021	0,405	0,716	0,084	-1,238	0,891	0,716	0,084	-0,871	-0,475
M, 39-64, HIGHER, EMPLOYED	Privacy	0,823	0,376	0,686	0,098	-0,917	-0,081	0,686	0,098	-0,745	-0,795
F, 18-39, HIGHER, EMPLOYED	Privacy	0,974	0,519	0,652	0,091	-0,726	-0,159	0,652	0,091	-0,578	-0,946
F, 39-64, HIGHER, EMPLOYED	Privacy	0,421	0,178	0,703	0,131	-1,118	-0,161	0,703	0,131	-0,864	-0,858

TABLE 12 DISTRIBUTION CHARACTERISTICS OF HOME DELIVERY MOTIVE SATISFACTIONS IN THE EMPIRICAL DATA AND ABM FOR THE EMPIRICALLY INFORMED SOCIO-DEMOGRAPHIC SEGMENTS.

Segment label	Motive	Beta		Empirical data				ABM			
		alpha	beta	mean	variance	skewness	kurtosis	mean	variance	skewness	kurtosis
M, 18-39, HIGHER, EMPLOYED	Convenient time	0,441	0,233	0,654	0,135	-0,523	-1,294	0,654	0,135	-0,627	-1,205
M, 39-64, HIGHER, EMPLOYED	Convenient time	0,662	0,251	0,725	0,104	-0,796	-0,917	0,725	0,104	-0,957	-0,510
F, 18-39, HIGHER, EMPLOYED	Convenient time	0,368	0,160	0,698	0,138	-0,667	-1,248	0,698	0,138	-0,842	-0,938
F, 39-64, HIGHER, EMPLOYED	Convenient time	0,701	0,172	0,803	0,085	-1,603	1,902	0,803	0,085	-1,451	0,793
M, 18-39, HIGHER, EMPLOYED	Low environmental impact	1,226	0,758	0,618	0,079	-0,180	-1,158	0,618	0,079	-0,421	-0,991
M, 39-64, HIGHER, EMPLOYED	Low environmental impact	1,723	1,034	0,625	0,062	-0,008	-0,982	0,625	0,062	-0,421	-0,823
F, 18-39, HIGHER, EMPLOYED	Low environmental impact	0,979	0,542	0,644	0,091	-0,504	-0,657	0,644	0,091	-0,540	-0,986
F, 39-64, HIGHER, EMPLOYED	Low environmental impact	1,253	0,552	0,694	0,076	-1,122	0,938	0,694	0,076	-0,742	-0,595
M, 18-39, HIGHER, EMPLOYED	Good working conditions	0,753	0,323	0,700	0,101	-0,776	-0,704	0,700	0,101	-0,818	-0,715
M, 39-64, HIGHER, EMPLOYED	Good working conditions	1,479	0,523	0,739	0,064	-0,592	-1,087	0,739	0,064	-0,940	-0,138
F, 18-39, HIGHER, EMPLOYED	Good working conditions	0,576	0,244	0,702	0,115	-0,922	-0,532	0,702	0,115	-0,846	-0,778
F, 39-64, HIGHER, EMPLOYED	Good working conditions	1,195	0,288	0,806	0,063	-1,451	1,895	0,806	0,063	-1,400	0,945
M, 18-39, HIGHER, EMPLOYED	Low delivery costs	1,839	1,481	0,554	0,057	0,042	-0,222	0,554	0,057	-0,170	-0,913
M, 39-64, HIGHER, EMPLOYED	Low delivery costs	1,995	1,244	0,616	0,056	0,156	-0,906	0,616	0,056	-0,375	-0,785
F, 18-39, HIGHER, EMPLOYED	Low delivery costs	1,197	0,827	0,591	0,080	-0,370	-0,686	0,591	0,080	-0,321	-1,070
F, 39-64, HIGHER, EMPLOYED	Low delivery costs	1,482	0,728	0,671	0,069	-0,558	-0,486	0,671	0,069	-0,618	-0,689
M, 18-39, HIGHER, EMPLOYED	Privacy	1,198	0,564	0,680	0,079	-0,629	-0,378	0,680	0,079	-0,682	-0,709
M, 39-64, HIGHER, EMPLOYED	Privacy	1,566	0,746	0,677	0,066	-0,296	-0,834	0,677	0,066	-0,640	-0,630
F, 18-39, HIGHER, EMPLOYED	Privacy	1,482	0,746	0,665	0,069	-0,203	-1,116	0,665	0,069	-0,595	-0,718
F, 39-64, HIGHER, EMPLOYED	Privacy	1,304	0,520	0,715	0,072	-0,704	-0,163	0,715	0,072	-0,836	-0,413

TABLE 13 DISTRIBUTION CHARACTERISTICS OF PARCEL LOCKER MOTIVE SATISFACTIONS IN THE EMPIRICAL DATA AND ABM FOR THE EMPIRICALLY INFORMED SOCIO-DEMOGRAPHIC SEGMENTS.

Segment label	Motive	Beta		Empirical data				ABM			
		alpha	beta	mean	variance	skewness	kurtosis	mean	variance	skewness	kurtosis
M, 18-39, HIGHER, EMPLOYED	Convenient time	1,781	0,159	0,918	0,026	-2,114	3,359	0,918	0,026	-2,652	7,200
M, 39-64, HIGHER, EMPLOYED	Convenient time	2,481	0,137	0,948	0,014	-2,491	5,814	0,948	0,014	-3,313	12,467
F, 18-39, HIGHER, EMPLOYED	Convenient time	2,384	0,048	0,980	0,006	-4,305	18,763	0,980	0,006	-5,795	39,989
F, 39-64, HIGHER, EMPLOYED	Convenient time	1,384	0,068	0,953	0,018	-2,948	7,517	0,953	0,018	-3,879	16,152
M, 18-39, HIGHER, EMPLOYED	Low environmental impact	2,697	0,938	0,742	0,041	-0,557	-0,439	0,742	0,041	-0,845	0,006
M, 39-64, HIGHER, EMPLOYED	Low environmental impact	3,372	1,221	0,734	0,035	-0,030	-1,344	0,734	0,035	-0,760	-0,037
F, 18-39, HIGHER, EMPLOYED	Low environmental impact	2,065	0,603	0,774	0,048	-1,267	1,899	0,774	0,048	-1,075	0,368
F, 39-64, HIGHER, EMPLOYED	Low environmental impact	1,525	0,360	0,809	0,054	-1,563	2,984	0,809	0,054	-1,373	1,021
M, 18-39, HIGHER, EMPLOYED	Good working conditions	2,902	0,480	0,858	0,028	-1,219	0,919	0,858	0,028	-1,596	2,281
M, 39-64, HIGHER, EMPLOYED	Good working conditions	3,712	0,509	0,880	0,020	-1,242	0,805	0,880	0,020	-1,713	2,960
F, 18-39, HIGHER, EMPLOYED	Good working conditions	2,107	0,206	0,911	0,025	-3,450	15,669	0,911	0,025	-2,435	6,089
F, 39-64, HIGHER, EMPLOYED	Good working conditions	2,695	0,195	0,932	0,016	-2,063	3,886	0,932	0,016	-2,779	8,596
M, 18-39, HIGHER, EMPLOYED	Low delivery costs	1,559	0,720	0,684	0,066	-0,826	0,431	0,684	0,066	-0,670	-0,591
M, 39-64, HIGHER, EMPLOYED	Low delivery costs	1,668	0,563	0,748	0,058	-0,925	0,642	0,748	0,058	-0,969	-0,008
F, 18-39, HIGHER, EMPLOYED	Low delivery costs	3,495	0,874	0,800	0,030	-0,732	-0,662	0,800	0,030	-1,091	0,730
F, 39-64, HIGHER, EMPLOYED	Low delivery costs	2,162	0,501	0,812	0,042	-0,668	-1,297	0,812	0,042	-1,310	1,059
M, 18-39, HIGHER, EMPLOYED	Privacy	2,053	0,634	0,764	0,049	-0,537	-0,735	0,764	0,049	-1,019	0,228
M, 39-64, HIGHER, EMPLOYED	Privacy	2,301	0,651	0,780	0,044	-0,230	-1,663	0,780	0,044	-1,083	0,455
F, 18-39, HIGHER, EMPLOYED	Privacy	2,542	0,917	0,735	0,044	0,003	-1,631	0,735	0,044	-0,823	-0,070
F, 39-64, HIGHER, EMPLOYED	Privacy	1,800	0,355	0,835	0,044	-0,842	-1,057	0,835	0,044	-1,546	1,725

Concerning the parcel demand generation, this is based on the zonal information and demand parameters provided by the Thessaloniki LL. In this module, courier market shares, depot location of the main courier companies and several parameters on income levels and parcels success rate are used.

Figure 18 below illustrates the inputs and outputs of the parcel demand module of MASS-GT.

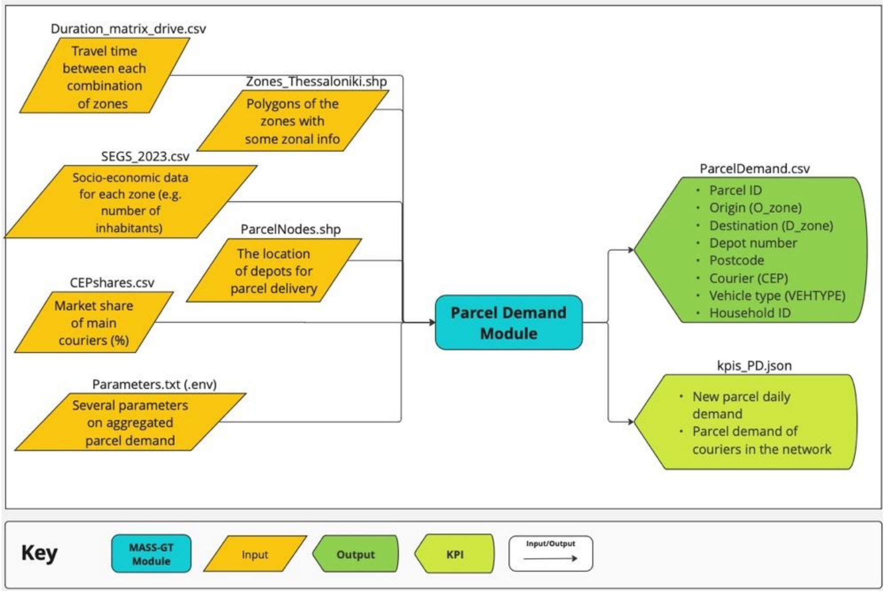

FIGURE 18 MASS-GT PARCEL DEMAND MODULE CALIBRATED FOR THESSALONIKI LL

The Parcel Market module receives the input on consumer choices for fulfilment types either PL or home delivery (traditional). This module allocates the parcels from the closest courier depot to the PL facility. Figure 19 below illustrates the inputs and outputs of the parcel market module of MASS-GT.

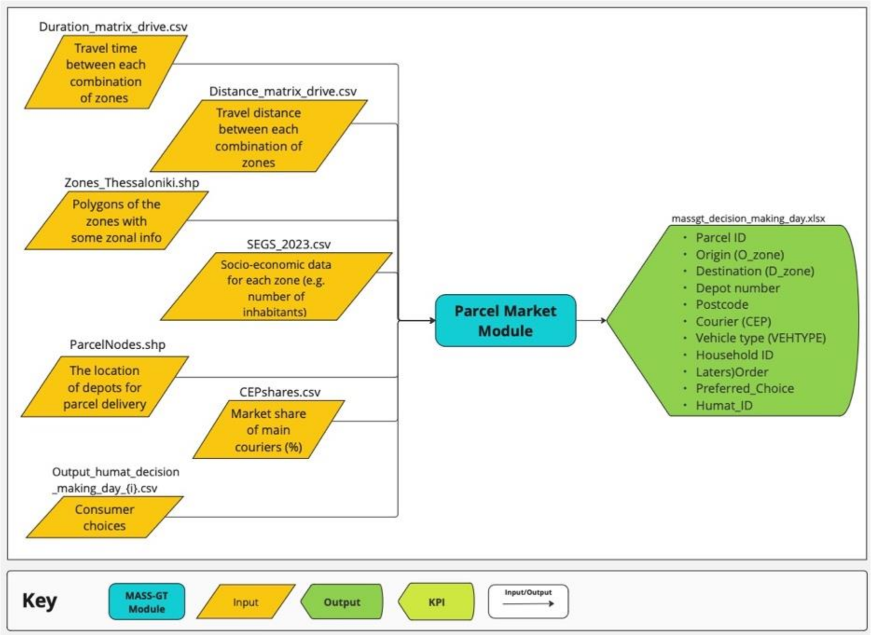

FIGURE 19 MASS-GT PARCEL MARKET MODULE CALIBRATED FOR THESSALONIKI LL

The Parcel Scheduling module generates delivery schedules for the parcels. This procedure considers the shortest path algorithm to distribute parcels in a tour, starting from a courier depot and ending at the same depot. The algorithm also considers the number of stops within a zone, as multiple deliveries are made in one zone. For each home delivery a portion of the intrazonal distance is considered. Since PLs provide a consolidation of parcels at an intermediate location for these deliveries the intrazonal distance is not included in the calculation. Figure 20 below illustrates the inputs and outputs of the parcel scheduling module of MASS-GT.

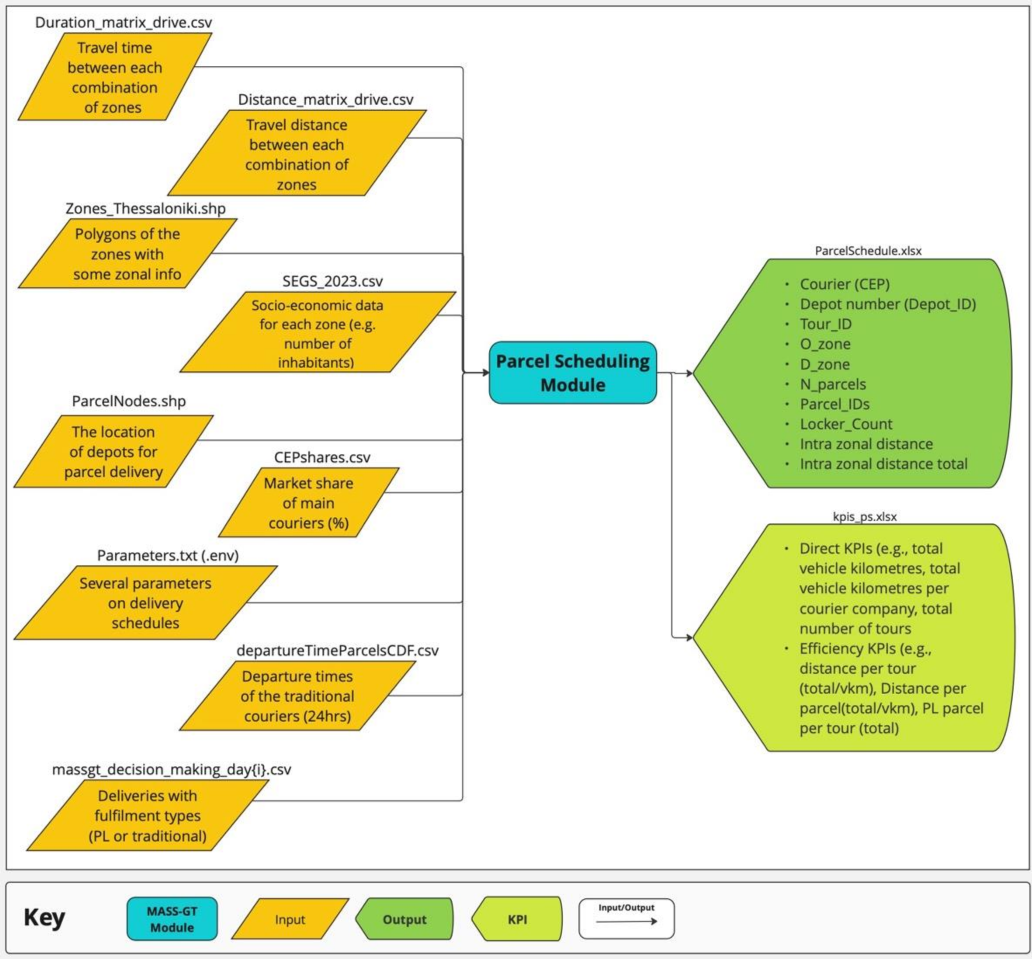

FIGURE 20 MASS-GT PARCEL SCHEDULING MODULE CALIBRATED FOR THESSALONIKI LL

The Decision Making and Opinion Diffusion module of HUMAT generates decisions of HUMAT agents. Figure 21 below illustrates the inputs and outputs of this module.

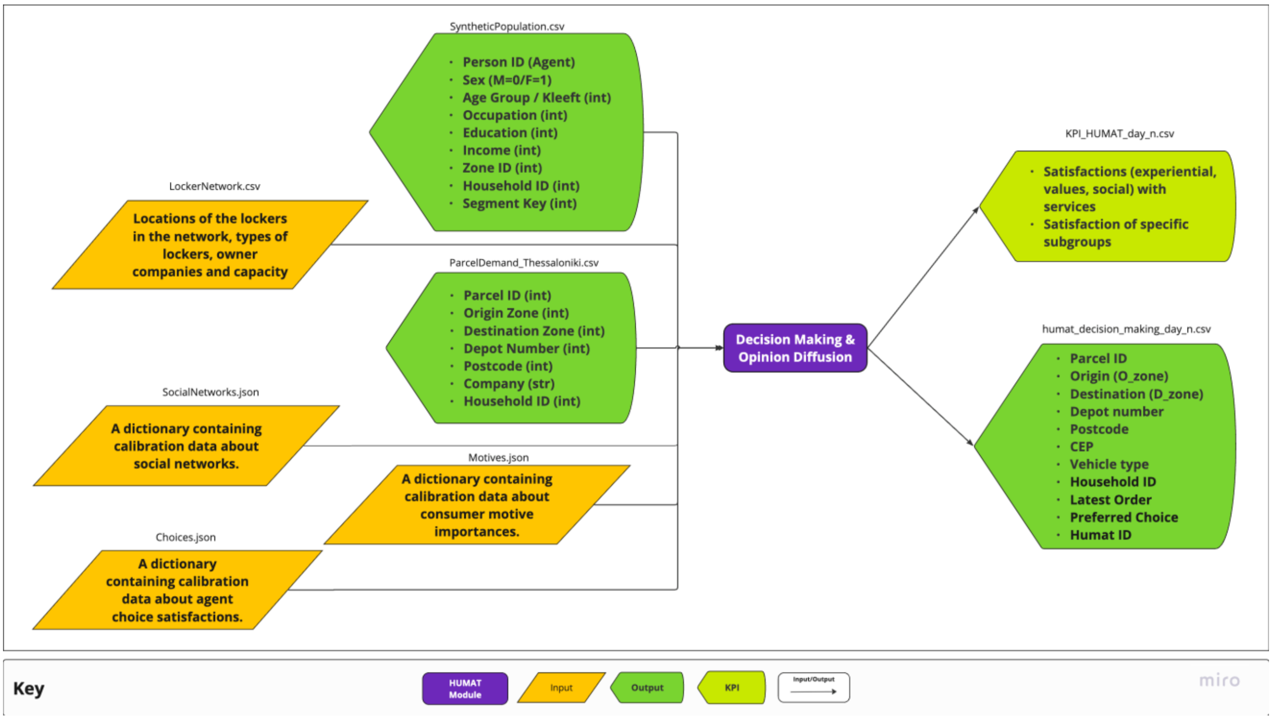

Figure 21 HUMAT Decision Making and Opinion Diffusion Module Calibrated for the Thessaloniki LL

KPIs of MASS-GT:

- **Number of parcels in the network:** This KPI
-
- tracks the total quantity of parcels that are currently within the distribution network managed by MASS-GT. It provides an overview of the volume of parcels being handled.
- **Number of parcels per courier**: This measures the average number of parcels that each courier in the network is responsible for delivering. It helps in assessing the workload distribution among couriers.
- **Number of tours per courier company**: This tracks how many delivery rounds or tours each courier company is making. It gives insight into the operational efficiency and scheduling of deliveries.
- **Total vehicle kilometres per courier company:** This measures the total distance travelled by the vehicles of each courier company in the network. It's a key metric for understanding operational costs, fuel consumption, and environmental impact.
- **CO2 emissions based on each company:** This KPI tracks the carbon dioxide emissions generated by the courier companies within the network. It is crucial for assessing the environmental footprint of the delivery operations and aligning with sustainability goals.

KPIs of HUMAT:

- **Customer satisfaction with locker and traditional delivery option**: This KPI measures how satisfied customers are with both locker-based and traditional delivery methods. It is essential for understanding customer preferences and improving service quality.

- **Used and available capacities of lockers (see above)**: This tracks how much of the locker capacity is being utilized versus how much is available. It helps in optimizing the allocation and deployment of lockers within the network, ensuring they are neither underutilized nor overburdened.
- **Number of lockers being fulfilled**: This indicates how many PLs are being utilized for parcel deliveries. This KPI could be used to understand the efficiency and utilization rate of the PL system.

6.2. Autonomous Delivery Vehicle Service (Helsinki LL)

6.2.1. System Overview and Motivations

The Helsinki LL has multiple piloting locations in the city of Helsinki, in Finland. The main objective of this LL is to achieve carbon neutrality by implementing the Carbon-Neutral 2035 Action Plan (*The Carbon-neutral Helsinki 2035 Action Plan*, 2018). Helsinki LL proposed testing the concept of micro hubs in the city, specifically focusing on innovative LMD options such as robot deliveries using ADVs, cargo bikes and teleoperation.

To explore the acceptability of ADVs, the modelling framework given in Section 5 can be calibrated and used for such a use case. In this use case, while the HUMAT modules simulate consumer choices between the ADV service and home delivery options over time, MASS-GT is used only to generate household demand since MASS-GT is not capable of simulating the ADV use case. Hence, we decided to combine HUMAT with SKEMA's vehicle routing model (VRP) in the calibrated modelling framework.

Several motivations behind the choice of the Helsinki LL are as follows:

- The LL aims to explore and assess willingness to accept services, particularly ADVs.
- The Helsinki LL aims to evaluate the impact of ADVs, including factors like demand variations under different scenarios.
- To this aim, the integrated modelling architecture facilitates the estimation of the uptake of ADVs.

6.2.2. Data Preparation for the ADV Service

MASS-GT Data

TABLE 14 MASS-GT DATA FOR HELSINKI LL

Category	Data name	Data type	Description	Used by
Network Data	Zones	Shape file	Centroids representing the zonal network of the study area	Parcel demand
	Parcel nodes	Shape file	Point vector showing the depot locations of the courier companies in the network	
	Duration matrix	.csv text	Duration matrix (in seconds) between each combination of the zone	
Demand data	Sociodemographic characteristics	.csv text	Population characteristics in the study area	

	Courier market shares	.csv text	Market shares of the courier companies in the network	

HUMAT data

TABLE 15 HUMAT DATA FOR HELSINKI LL

Category	Dataset name	File type	Description	Used by
Synthetic Population Data	SyntheticPopulation	.csv	A list of agents with parameters representing the population of the Helsinki LL.	Decision Making & Opinion Diffusion
Fulfilment Data	ADV_Capacity	.csv	A table with parameters for delivery locations visited by ADV.	
Social Network Data	SocialNetwork	.json	A dictionary containing calibration data about social networks.	
Consumer Motives Data	Motives	.json	A dictionary containing calibration data about consumer motive importances.	
	Choices	.json	A dictionary containing calibration data about agent choice satisfactions.	

Synthetic population Data

Synthetic populations are produced from EU-SILC 2022 living condition data from Finland and Greece give attributes to agents in the model. Full-scale populations of people aged 16+ for the municipalities of Helsinki and Thessaloniki come from Wasserstein generative adversarial networks trained on EU-SILC data. The annex describes data and methods in detail (Annex III).

Fulfilment Data

The fulfilment data ("ADV_Capacity.csv") contains detailed information about the PL network in Helsinki (Tab. 16). The setting data, provided by VRP, is used as an input in all simulation scenarios. Each row of the file provides information about a single ADV stop. Stop is characterized by location coordinates ("Lat/Lon"), a zone id ("Areanr"), a parcel capacity (Capacity), a status (Status_type).

TABLE 16 STRUCTURE OF THE FULFILMENT DATA INPUT

Variable	Description	Type	Possible values
Cep	Indicates the operation Company of a ADV delivery location.	string	DBS
Areanr	Indicates the zone id of ADV delivery location.	integer	2, 4, 5, 9, 19, 30, 31, 32, 33
Capacity	Indicates the maximum possible capacity of parcels that can be delivered to a location.	Integer	0-300

Status_type	Indicates that the location can used by all ADVs.	string	public

Social Network Data

Social network data contains information to configure social networks in which humat agents communicate with other humat agents. The social network data is arranged in the form of a dictionary and saved in .json format ("SocialNetworks.json"). Social network data is following the same structure and rules as described in Section 6.1.2 (see Table 6).

Consumer Motives Data

Consumer Motives Data ("motives.json", "choices.json") were used in simulation scenarios and are described in Section 7.1, (Table 8). The motive and fulfilment type satisfaction for all socio-demographic segments, defined by a combination of sex (M, F), age group (18-39, 40-64, 65+), education level (not higher education, higher education) and employment status (not employed, employed), are defined in the scenario.

VRP Data

TABLE 17 VRP DATA FOR HELSINKI LL

Category	Dataset name	File type	Description
Parcel Data	ParcelDemand	.csv	A list of parcels to be delivered and the locations they are to be delivered to
Electricity Generation Breakdown	Electricity	.xslx	A table with parameters describing the different sources used to generate electricity, the emissions factor associated with each source.
Robot	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	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.

For a simulation run, the VRP simulates the operation of the ADV and outputs:

The time at which the robot arrives at each delivery point
The number of parcels delivered at each delivery point
The percentage of parcels successfully delivered at each delivery point
The average waiting time at each delivery point
The average queue length at each delivery point
The total emissions (in gCO2eq, estimated carbon emissions) during the delivery operation
The total distance (in kilometres) travelled during the operation

6.2.3. Calibrated and Validated ABM for the ADV Service

Calibration refers to fine-tuning software components to achieve desired output levels of the selected use case. This might involve setting parameters, fine-tuning inputs and outputs, adjusting algorithms, or optimizing configurations to meet specific criteria. This process ensures that the model accurately represents the use case being studied.

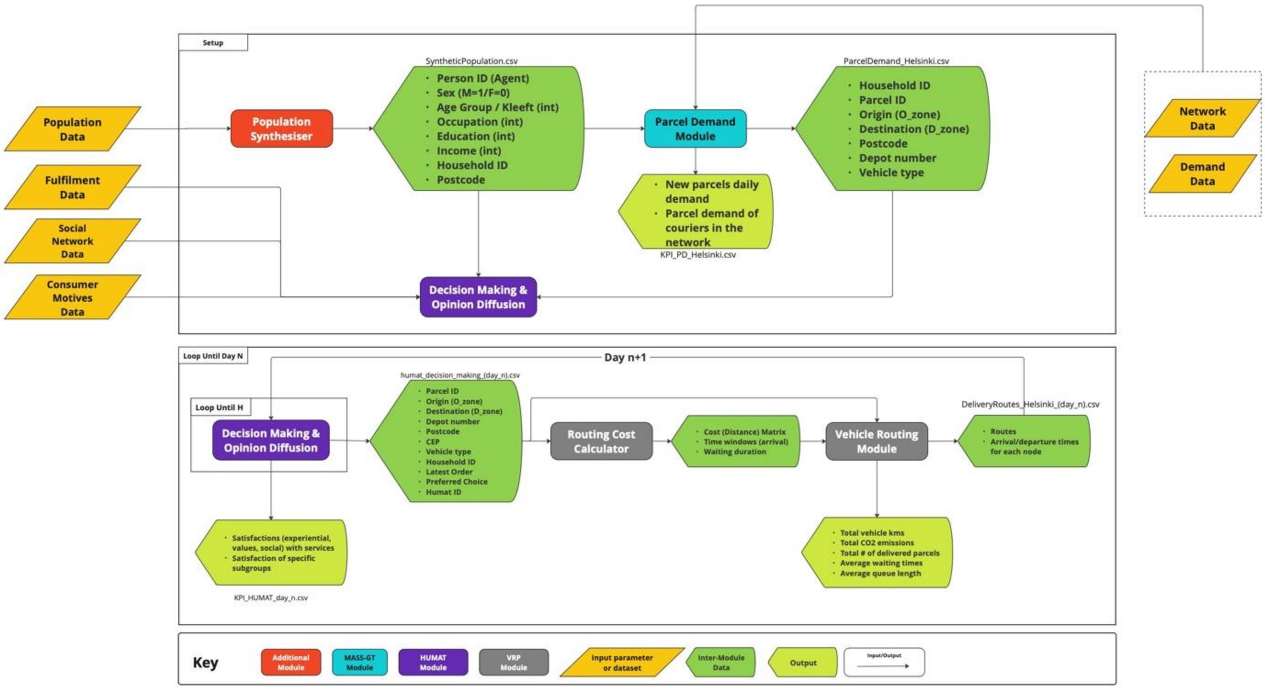

FIGURE 22 MODELLING FRAMEWORK CALIBRATED FOR HELSINKI LL

The integrated HUMAT and MASS-GT models are calibrated and conceptualized as depicted in Figure 26. In the Helsinki LL, three models are used. Like the previous use cases, HUMAT is applied to model the acceptance of ADVs. In this use case, MASS-GT is used only in the generation of parcel demand. The reasons include (1) the dynamic nature of ADVs as a delivery method, (2) the mismatch of aggregation levels between MASS-GT and ADVs. Lastly, VRP model is used to generate the optimal route of ADVs.

Synthetic Population Data

The synthetic population is comprised of 24 socio-demographic segments defined by a combination of sex (M, F), age group (18-39, 40-64, 65+), education level (not higher education, higher education) and employment status (not employed, employed). The data only concern the population of 8 district of Helsinki (postcodes: 100, 120, 150, 180, 220) and displays the population in a 1/10 ratio (3142 agents).

TABLE 18 SOCIO-DEMOGRAPHIC SEGMENT SHARES IN THE SYNTHETIC POPULATION OF THESSALONIKI

Socio-demographic segment	Frequency	Percent
M, 18-39, NOT HIGHER, NOT EMPLOYED	191	6.1

M, 18-39, NOT HIGHER, EMPLOYED	304	9.7
M, 18-39, HIGHER, NOT EMPLOYED	50	1.6
M, 18-39, HIGHER, EMPLOYED	294	9.4
M, 40-64, NOT HIGHER, NOT EMPLOYED	6	0.2
M, 40-64, NOT HIGHER, EMPLOYED	171	5.4
M, 40-64, HIGHER, NOT EMPLOYED	4	0.1
M, 40-64, HIGHER, EMPLOYED	157	5
M, 65+, NOT HIGHER, NOT EMPLOYED	113	3.6
M, 65+, NOT HIGHER, EMPLOYED	88	2.8
M, 65+, HIGHER, NOT EMPLOYED	48	1.5
M, 65+, HIGHER, EMPLOYED	76	2.4
F, 18-39, NOT HIGHER, NOT EMPLOYED	228	7.3
F, 18-39, NOT HIGHER, EMPLOYED	251	8
F, 18-39, HIGHER, NOT EMPLOYED	86	2.7
F, 18-39, HIGHER, EMPLOYED	313	10
F, 40-64, NOT HIGHER, NOT EMPLOYED	4	0.1
F, 40-64, NOT HIGHER, EMPLOYED	128	4.1
F, 40-64, HIGHER, NOT EMPLOYED	6	0.2
F, 40-64, HIGHER, EMPLOYED	173	5.5
F, 65+, NOT HIGHER, NOT EMPLOYED	120	3.8
F, 65+, NOT HIGHER, EMPLOYED	72	2.3
F, 65+, HIGHER, NOT EMPLOYED	131	4.2
F, 65+, HIGHER, EMPLOYED	128	4.1
Total	3142	100

Fulfilment Data

Calibration used in the baseline scenarios is provided by the Helsinki LL. The file contains 1 ADV that has pick up stops in 5 districts of Helsinki (postcodes: 100, 120, 150, 180, 220).

Social Network Data

Due to lack of empirical data describing the topology of social networks in Helsinki, the ABM was not empirically calibrated to the Helsinki LL use case with respect to this aspect. The rules for generating social networks followed the description from Section 6.1.2.

Consumer Motives Data

In the process of calibrating the model, the data on motive importances and fulfilment type motive satisfactions is described is not empirically evaluated. It follows descriptions given in section 6.13. All humat agents in the Helsinki case are calibrated as indifferent customers with a beta-distribution with alpha = 5 and beta = 5 for all motives and segments.

ADV Robot Data

The ADV is configured by reading in information from three sources. The ADV emissions are calculated based on an electricity mix (Table 18). Characteristics of the ADV robot are set through inputs in the .env file. In the Helsinki L case the robot speed is set to 1.42, battery capacity to 7.

TABLE 19 ELECTRICITY GENERATION BREAKDOWN FOR CALCULATING ADV EMISSIONS

Source	Emission Factor	Generation Percentage
Coal	911	0.1001599
Natural gas	320	0.034707078
Nuclear	12	0.217281451
Hydroelectric Power	24	0.038183368
Wind Energy	11	0.017596455
Solar Energy	41	0.017596455
Biofuels and waste	230	0.337500373
Oil	720	0.236974921

During each day VRP model reads information from the humat decision making module, and selects those parcels which are ordered with delivery by the ADV. It computes the number of parcels going to each delivery location and generates the optimal route from the depot to these locations.

In the case of the Helsinki LL, the Parcel Demand module of MASS-GT has not been calibrated yet since the main input data is still missing. With respect to VRP model, the depot is assumed to be the starting point of the ADV. In the model, ADV visits the rest of the pick-up points within different time windows, as experimented in the VRPTW model, and then returns to the depot.

7 Simulations and Results

This section reports the simulation scenarios of the use cases given in Section 6 and the results obtained by executing them. We define a simulation scenario as a combination of input parameter values defined at the stage of model initialization. For each use case, a baseline scenario and various what-if scenarios are defined.

7.1. Parcel Locker Service (Thessaloniki LL)

7.1.1 Simulations

Simulations of the URBANE ABM are carried out through implementing 24 what-if scenarios in a DT of Thessaloniki with the population scaled 1:10. A what-if scenario is defined as a combination of 5 parameter values communicated to the model at the initialization. Table 20, summarizing the ABM simulation parameters and their settings, is followed by a description of parameter values. Next, a table of all scenarios is provided (Table 21).

TABLE 20 ABM SIMULATION PARAMETERS AND THEIR SETTINGS

Parameter	Settings
1. Parcel locker network	A. As is
2. Capacity	A. 34
	B. 68
3. Parcel locker type	A. Private/public mix
	B. Public
	C. Private
4. Emptying schedule	A. 100%
	B. 50%
5. Consumer satisfactions	A. Indifferent consumers
	B. Parcel locker preferred over home delivery

Parameter descriptions:

1. Parcel locker network

Changes to the PL network allow for testing different PL configurations related to courier companies. The parameter currently has a single baseline setting used in all simulation scenarios, the ***A. As is***, described in the form of a .csv file (*Locker network.csv*), which constitutes the content of the Fulfilment data input. In the ***As is*** setting, which reflects the status quo, Thessaloniki has 59 lockers (with defined locations) belonging to 3 companies (labelled 1,4,7). To change this parameter to a different setting, a new .csv file should be provided as input. Additional settings can reflect alternative states of affairs. For example, a what-if with a new service provider, Company 2, entering the Thessaloniki market and owning a single PL facility in a chosen location or a what-if with an existing provider expanding their infrastructure by adding an additional facility in a chosen location.

2. Capacity

Changes of the capacity parameter enable simulating various capacities of individual PLs. The baseline capacity is defined as 34 parcels (***A. 34***). The baseline setting is described in the form of a .csv file (*Locker network.csv*), which constitutes the content of the Fulfilment data input. Alternatively, the simulation doubles the capacity of PLs (***B. 68***), which requires changing the content of the .csv file. Additional settings can reflect what-ifs of a different uniform capacity value or capacities varying by PL.

3. Parcel locker type

Changes of PL type modify the utilization privileges (but not the ownership) of available PLs. Private lockers are operated by only one carrier. Public PLs are 'white label' and can be used by different carriers. The baseline PL type is a mix of private and public PLs (***A. Mix private/public***), is described in detail in the form of a .csv file (*Locker network.csv*), which constitutes the content of the Fulfilment data input. Simulated what-if scenarios assume a public type of all PLs (***B. Public***), where all companies have the right to use all PLs and a private type of all PLs (***C. Private***) where operating service providers are only allowed to use their own PLs. Additional settings can describe a what-if with any chosen structure of PL utilization privileges.

4. Emptying schedule

Changes of the emptying schedule alternate the fraction of PLs that are emptied daily. The baseline scenario (***A. 100%***) assumes that all parcels are collected by the end of the same day that they were deposited in a PL. The alternative setting reflects emptying an average of 50% (+/- 10) of lockers on the day of delivery (***B. 50%***). Informing this parameter with additional settings requires providing a new value that reflects the fraction of parcels emptied daily (optionally, with another value signifying a range of variance. The variance is implemented by randomly selecting from a uniform distribution of a given range).

5. Customer satisfactions

Changes of the consumer satisfactions parameter reflect changes in the structure of motivations and fulfilment type satisfactions among the socio-demographic segments of the urban population. Altering this setting requires modification to the content of the Consumer Motives Data. In the ***A. Indifferent consumers setting***, the motive importances and choice satisfactions of four socio-demographic customer segments (highly educated, employed males and females in age groups 18-39 and 40-64) informed by survey data. The remaining twenty socio-demographic customer segments (where empirical data is absent) assumed indifferent consumer satisfactions between home delivery and PL. Importances of motives and choice satisfactions assumed normally distributed around a neutral mean. The average socio-demographic segment motive importances and satisfactions are shown in Figure 23 and Figure 24, respectively.

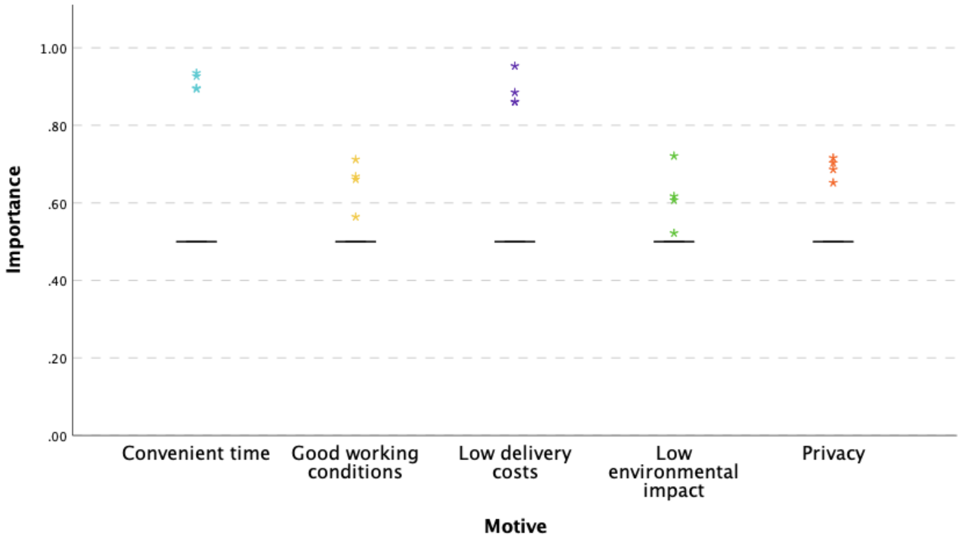

FIGURE 23 INDIFFERENT CUSTOMERS (5A): AVERAGE SOCIO-DEMOGRAPHIC SEGMENT IMPORTANCE BY MOTIVE.

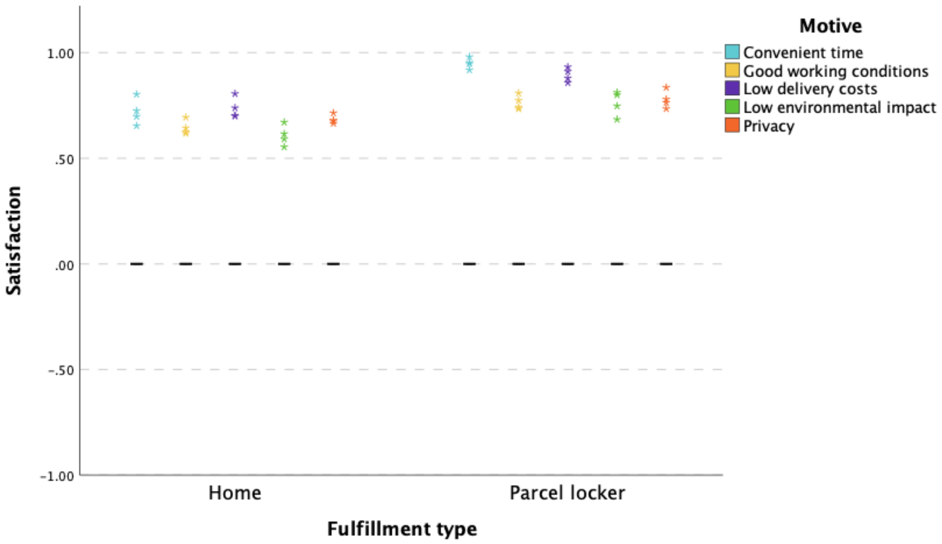

FIGURE 24 INDIFFERENT CUSTOMERS (5A): AVERAGE SOCIO-DEMOGRAPHIC SEGMENT SATISFACTION BY FULFILMENT TYPE AND MOTIVE.

In the ***B. Parcel locker preferred over home delivery*** setting the motive importances and choice satisfactions of four socio-demographic customer segments (highly educated, employed males and females in age groups 18-39 and 40-64) informed by survey data. The choice satisfactions in the entire population are like choice satisfactions among employed with higher education in the age group 18-64. The remaining twenty customer segments assumed identical to the most socio-demographically similar segment. Rules for motive importances formulated based on external studies and team discussion. The average socio-demographic segment motive importances and satisfactions are presented in Figure 25 and Figure 26, respectively.

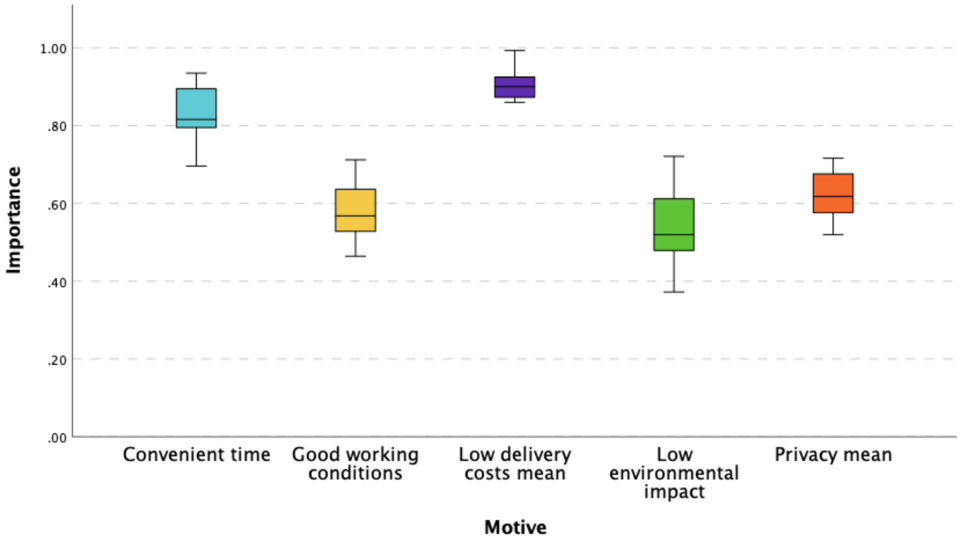

FIGURE 25 PARCEL LOCKER PREFERRED OVER HOME DELIVERY (5B): AVERAGE SOCIO-DEMOGRAPHIC SEGMENT IMPORTANCE BY MOTIVE.

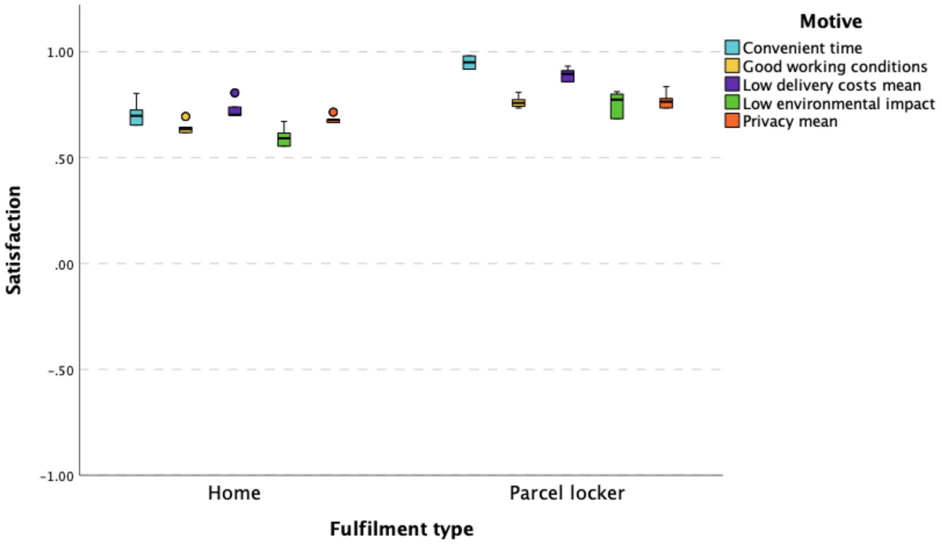

FIGURE 26 PARCEL LOCKER PREFERRED OVER HOME DELIVERY (5B): AVERAGE SOCIO-DEMOGRAPHIC SEGMENT SATISFACTION BY FULFILMENT TYPE AND MOTIVE.

Each of the 24 simulated scenarios is a unique combination of parameter settings. For example, scenario 1, which serves as a reference baseline scenario, is a combination of the first setting of all parameters (i.e., 1A, 2A, 3A, 4A, 5A) and represents a state of affairs with the status quo of the PL network (1A), with each PL having a capacity of 34 parcels (2A), the PLs are utilized by a mix of private and public service providers (3A), each PL is completely emptied by the end of the same that the parcel was deposited (4A) and most of the population is indifferent between a home delivery and a PL delivery (5). Table 21 lists the simulated scenarios.

TABLE 21 SIMULATION SCENARIO OF THESSALONIKI LL.

Scenario	1. PL Network	2. Capacity	3. PL Type	4. Emptying schedule	5. Consumer satisfactions
Scenario 1	1A	2A	3A	4A	5A
Scenario 2	1A	2A	3A	4B	5A
Scenario 3	1A	2A	3B	4A	5A
Scenario 4	1A	2A	3B	4B	5A
Scenario 5	1A	2A	3C	4A	5A
Scenario 6	1A	2A	3C	4B	5A
Scenario 7	1A	2B	3A	4A	5A
Scenario 8	1A	2B	3A	4B	5A
Scenario 9	1A	2B	3B	4A	5A
Scenario 10	1A	2B	3B	4B	5A
Scenario 11	1A	2B	3C	4A	5A
Scenario 12	1A	2B	3C	4B	5A
Scenario 13	1A	2A	3A	4A	5B
Scenario 14	1A	2A	3A	4B	5B
Scenario 15	1A	2A	3B	4A	5B
Scenario 16	1A	2A	3B	4B	5B
Scenario 17	1A	2A	3C	4A	5B
Scenario 18	1A	2A	3C	4B	5B
Scenario 19	1A	2B	3A	4A	5B
Scenario 20	1A	2B	3A	4B	5B
Scenario 21	1A	2B	3B	4A	5B
Scenario 22	1A	2B	3B	4B	5B
Scenario 23	1A	2B	3C	4A	5B
Scenario 24	1A	2B	3C	4B	5B

7.1.2 Results

Demand generation

As detailed in Section 4.3, the Parcel Demand module of MASS-GT estimates the demand based on various sociodemographic characteristics and the household structure of the population. Given the data gathered from the Thessaloniki LL, we have generated the demand per household in the study area. For this purpose, the main parameters used are provided in Table 22.

TABLE 22 MAIN DEMAND PARAMETERS FOR THE THESSALONIKI LL

Number of parcels (year)	45.3 million
Number of households	4.5 million

Number of working days	250
Parcel success rate	0.85
Income per zone	0.0058
Employment per zone	0.0000

In 2021 a total of 119 million parcels were delivered in Greece. Small packages (up to 2kg) constituted 38% of all deliveries (45.2 million parcels) (EETT, 2021). To indicate the magnitude of parcels delivered on an average working day, we have used the number of households in Greece, which is 4.5 million, and considered the number of working days in a year as 250. Dividing the number of parcels by the number of households and the number of working days results in the parcels per household. The parameter "PARCELS_PER_HH" is calculated as 45.2 / 250 / 4.50 parcels per hh per day.

The parameter "PARCELS_SUCCESS_B2C" is used to represent the proportion of successful deliveries on the first attempt, which has a value of 0.85 (based on the information received from the LL). Lastly, the parameter "INCOME_PER_ZONE," showing the regression coefficient, is calculated as 0.0058, established through a linear regression model (refer to Annex IV for more details). The specifications of the regression model are represented in Annex I. The parameter "PARCELS_PER_EMPL," representing the number of parcels based on employment characteristics, is set at 0.000 and is included for generalisation purposes due to the absence of data.

The parcel demand allocation to the courier depots is done with the help of network and supply data. The demand module allocates the parcels based on the courier market share information. Consequently, parcel origins are based on the courier depot location (parcel nodes) network. The origin of parcels is allocated to the closest depot of the courier company. The network, including the parcel nodes (depot locations), looks like the following:

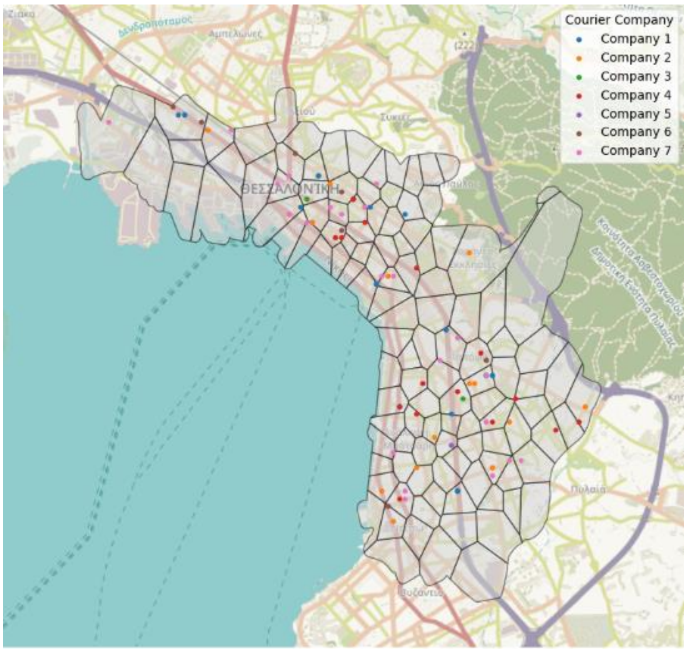

FIGURE 27 DEPOT LOCATIONS OF THE COURIERS

Given the parameters in Table 22 and the network data, the Parcel Demand module generated a daily demand of 9021 parcels over 120 zones for the study area. This generates an average daily demand for 75 parcels per zone. This average daily demand is validated by the LL given their market expertise on LMD demand in the Thessaloniki. The spatial distribution of parcel demand across the zones, highlighted in different categories based on the intensity of demand in Figure 28.

PLs are only available in 40 out of the 120 city zones. Zones with PLs account for almost 40% of the overall parcel demand (on average, 3523 of 9021 parcels), and zones without PLs account for slightly over 60% (on average, 5498 of 9021 parcels).

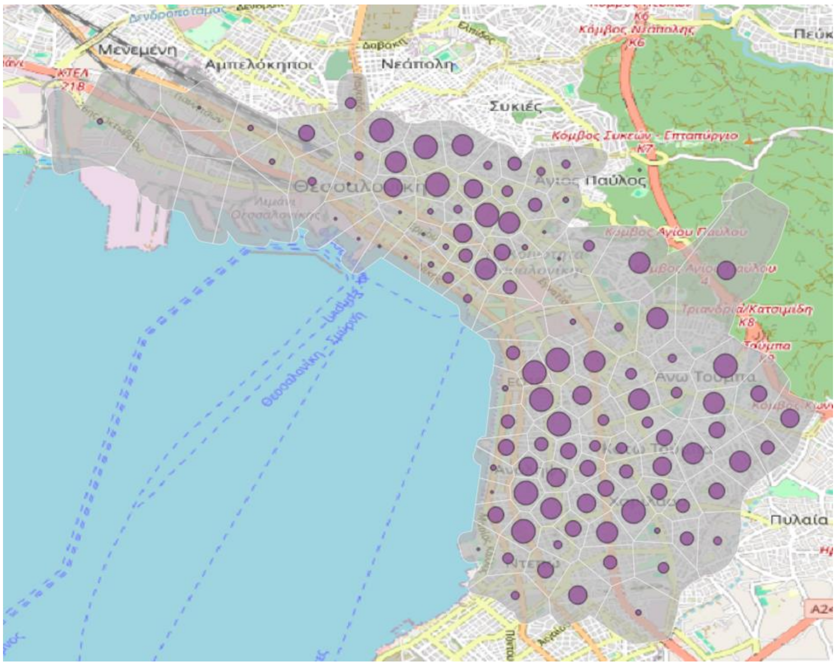

FIGURE 28 DEMAND DISTRIBUTION OF THE THESSALONIKI LL

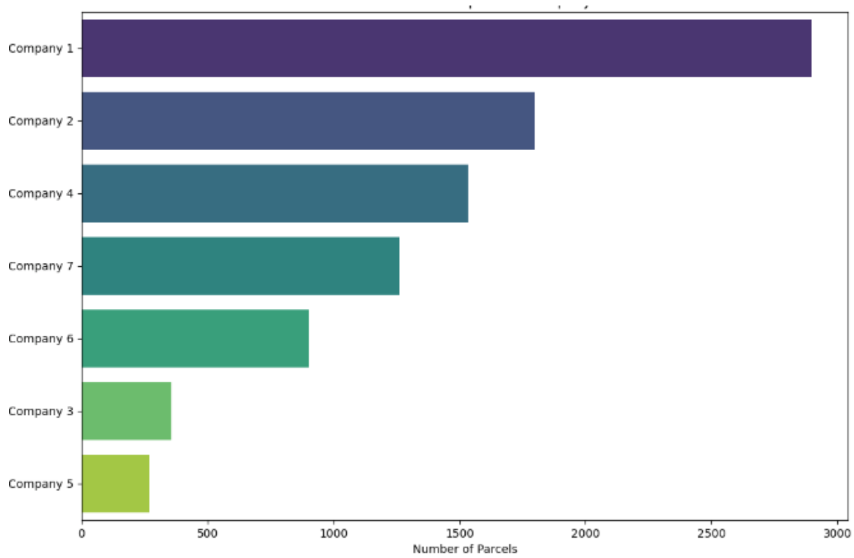

FIGURE 29 PARCEL DEMAND PER COURIER COMPANY IN THE NETWORK

The bar chart in Figure 29 provides a comparison of the simulated parcel demand on an average day for each of the courier companies in the network. The parcel demand for each company follows a similar structure to the courier market shares provided by the Thessaloniki LL, as could be expected from the model specification.

Parcel locker demand and utilization

Based on their motive structure, humat agents in the ABM choose their preferred fulfilment type. In the indifferent customer preference scenarios (scenario settings 5A), on average 53% of agents would like to have their parcel delivered via a PL. This fraction increases to 80% in the PL preferred over home delivery scenarios (scenario settings 5B). It is important to point out that the demand for PLs is independent of other scenario parameter settings such as PL capacity, PL type or the emptying schedule. Therefore, in figures Figure 30, Figure 32 (representing the indifferent customer preference scenarios[10]), and in figures Figure 59 and Figure 60 (representing the PL preferred scenarios), the demand for PLs fluctuates only marginally over the course of one simulation. The fluctuation is a result of minor changes in consumer perceptions of home deliveries and PLs originating in social network information exchanges about the two fulfilment types.

Regardless of customer preferences, parcels are ultimately delivered via a fulfilment type that is available at a given time step. As a result, humat agents living in the zones without PLs have their parcels delivered home (even though some prefer a PL delivery). Humat agents living in zones where PLs are available, only get to use them if their preferred PL has not yet reached its full capacity. Further results describe a comparison between PL demand and PL usage focusing on the 44 zones where PLs are available (Figure 31 and Figure 33).

Indifferent customers and low parcel locker capacity

When most of the consumers are indifferent between a PL and a home delivery, the zones with PL infrastructure experience a PL demand of approx. 1878 parcels per day. This constitutes approx. 53% of the 3523 ordered parcels.

In the scenarios with a PL capacity of 34 (6 scenarios in Figure 30: 3,1,5,4,2,6), the highest daily number of PL orders is reached when the infrastructure is shared among all service providers (setting: only public PL). As suggested by the PI concept (Faugere and Montreuil, 2016 & URBANE D1.1 URBANE framework for optimised green last mile operations) and validated by our analysis, the open PL infrastructure is a significant enabler of efficient use of the existing infrastructure. The PL orders fluctuate around an average of 1403 parcels delivered every day in a setting with 100% of PLs emptied daily and 922 parcels in a setting with 50% of PLs emptied daily. The infrastructure usage decreases significantly when the ownership changes to a mix of private and public PLs. The drop is around -44% and -34% for the respective emptying schedules. The decrease in parcels delivered daily to PLs is even more profound when comparing the only public and only private PL scenario settings, with a drop of -73% and -58% for the respective emptying schedules.

As expected, the emptying schedule also influences the usage of the PL infrastructure, as the number of parcels added daily to PLs decreases with lower emptying rates. The underusage of PLs in the only private scenario setting is so profound (a drop to approx. 384 parcel orders daily) that the emptying schedule ceases to influence PL usage.

[10] Scenarios 1,2,3,4,5,6,7,8,9,10,11,12 in Table 21.

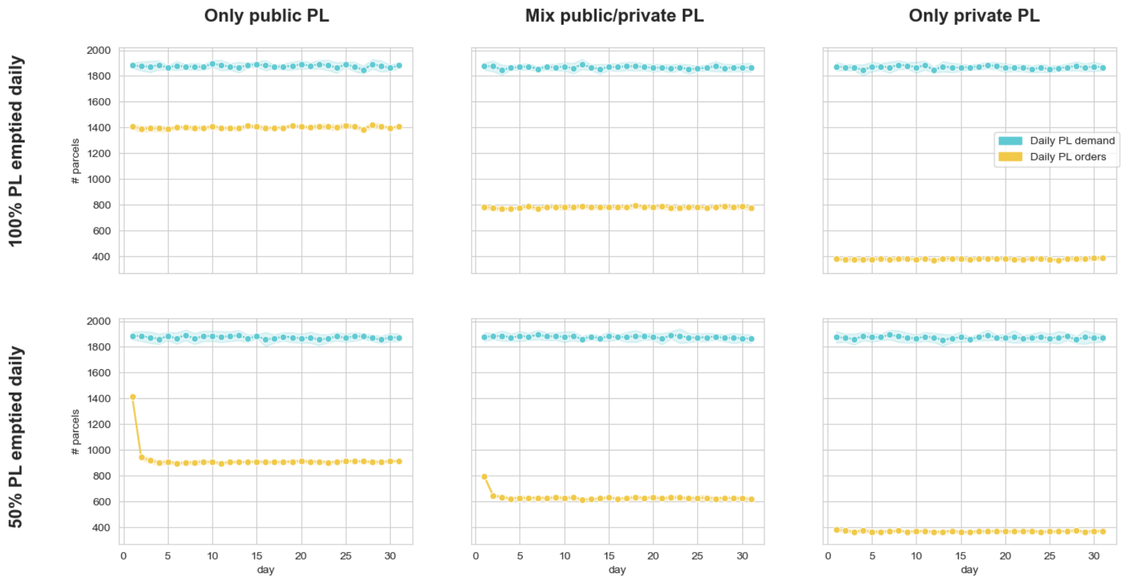

FIGURE 30 PL DEMAND AND PL ORDERS FOR INDIFFERENT CONSUMERS (5A) AND PLS WITH A CAPACITY OF 34 PARCELS (2A). RELEVANT SCENARIOS: 3, 1, 5, 4, 2, 6.

The PL demand - the number of customers who prefer PL fulfilment type. The PL orders - the number of parcels added to parcel lockers. In 100% PL emptied daily settings, all ordered parcels are picked up by customers on the same day. In the 50% PL emptied daily settings, half of the parcels stored in a PL (a sum of newly ordered and not picked-up leftover parcels from previous days) are picked up daily. In only public PL settings, all companies have the right to use the parcel lockers. In only private PL, only the PL owner can use their own PL.

The analysis of PL utilization focuses on the PL usage from the perspective of the city zones, and sheds new light on the optimization of the infrastructure (see Figure 31). The utilization analyses are coherent with PL order analysis described above and show a clear advantage of PL sharing schemes. Scenario settings with only public PL showcase the highest utilization of the PL infrastructure, which in turn allows for the highest numbers of daily orders to PLs. The emptying schedule significantly influences utilization, with less parcels picked up daily quickly overburdening the infrastructure and thus limiting the number of parcels that can be added to a PL. When all companies have access to infrastructure (only public PL) and the entire content of PLs is emptied daily (100% PL emptied daily; top left of Figure 31), 90% or higher utilization is reached in 28 city zones. Such a high utilization rate is observed in 9 additional zones when only half of the PL content gets picked up (50% PL emptied daily; bottom left of Figure 31). When PLs are used only by their owners, the non-collaborative service providers are worse off. Not only are the PL orders very low, but the entire infrastructure is heavily underutilized. With 100% of parcels picked up each day, there are no zones where 90% utilization is observed. In fact, the highest utilization rate of 74% occurs in zone 48. With 50% of PL content emptied daily, utilization in zone 48 goes up to over 99%, and three additional zones reach the 90% utilization threshold.

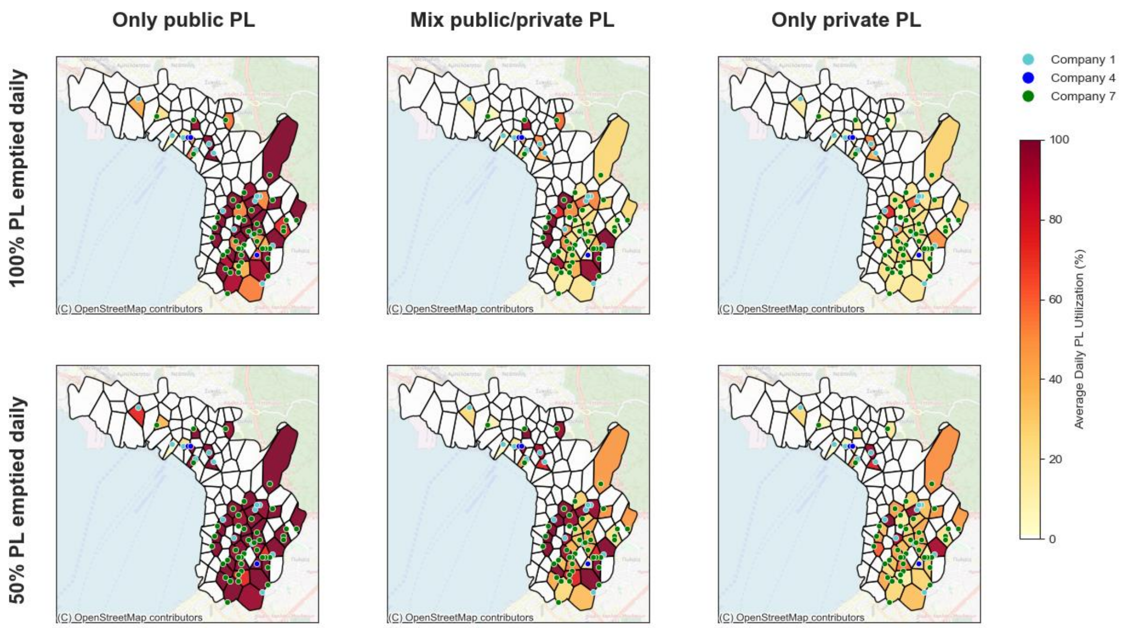

FIGURE 31 PARCEL LOCKER UTILISATION FOR INDIFFERENT CONSUMER (5A) AND PARCEL LOCKERS WITH A CAPACITY OF 34 PARCELS (2A). RELEVANT SCENARIOS: 3, 1, 5, 4, 2, 6.

The average daily PL utilization is presented per zone and indicates the average percentage of occupied parcel slots over the 31 days of simulation in all the parcel lockers that are in a given zone. In the scenarios of 34 parcel capacity,100% average utilization means that all 34 parcel slots are taken in all parcel lockers in a particular zone. On the other hand, 0% utilization means that in all parcel lockers in each zone, 34 parcel slots are vacant. A slot can be occupied either by a newly delivered parcel or by a parcel delivered earlier, which has not yet been picked up.

Indifferent customers and high parcel locker capacity

Increasing the capacity of PL to 68 naturally increases the number of orders that can be fulfilled via PL. Interestingly, it allows the PL capacity to almost adequately respond to customer demand in a single scenario of shared PL and all parcels emptied daily (scenario 9). The number of parcels delivered daily to PLs reaches an average of 1825, while the demand is at 1861. In the remaining scenarios that entail indifferent customers and high PL capacity, the situation is like the low PL capacity settings (described in the sub-section above):

- the demand heavily exceeds the supply (5 scenarios in Fig. 31: 7, 11, 10, 8, 12),
- collaborative action of sharing the infrastructure (public PL settings) allows all companies to deliver more via this fulfilment type,
- low fraction of PL content emptied daily negatively impacts PL usage in the public and mix public/private PL scenario settings (compared to 100% PL emptied daily, drops by 23% and 8%, respectively),
- the higher capacity of 68 does not influence the results at all in the private PL scenario settings, as a similar dramatic drop to only 399 parcel orders delivered to PLs daily is observed.

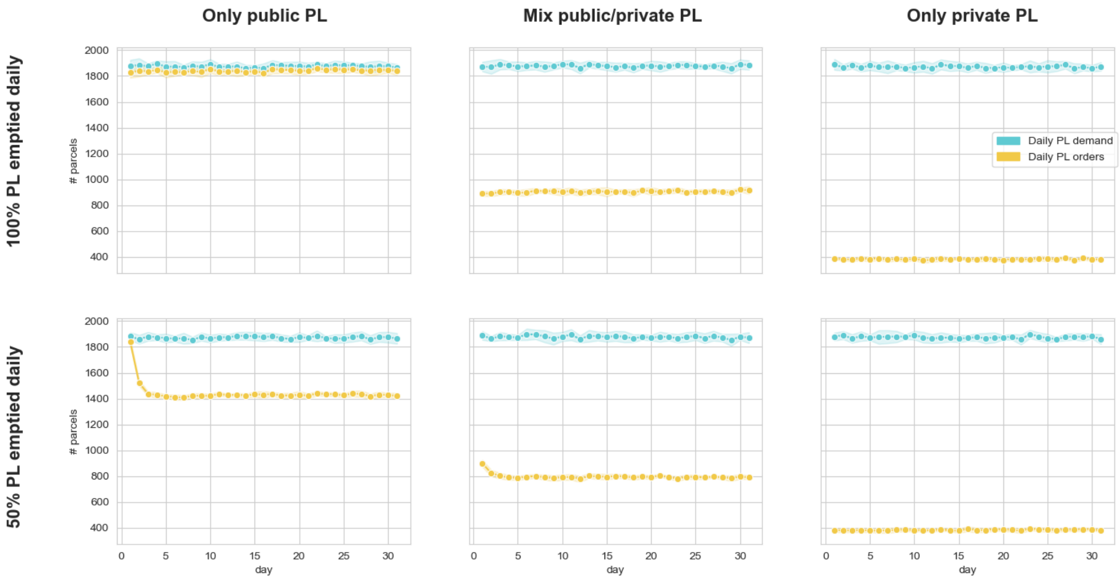

FIGURE 32 PARCEL LOCKER DEMAND AND USAGE OF INDIFFERENT CONSUMERS (5A) IN ZONES WITH PARCEL LOCKERS, PARCEL LOCKERS HAVE A CAPACITY OF 68 PARCELS (2B). RELEVANT SCENARIOS: 9, 7, 11, 10, 8, 12.

The impact of increasing PL capacity on the infrastructure utilization is profound. In scenario 9 (top left of Fig. 32: only public PL, 100% PL emptied daily), the 90% or higher utilization is observed in 5 city zones, 23 zones less compared to the same settings and PL capacity of 34. The number of zones with heavily utilized PL infrastructure increase to 24 when the daily emptied content decreases in half (bottom left of Fig. 32).

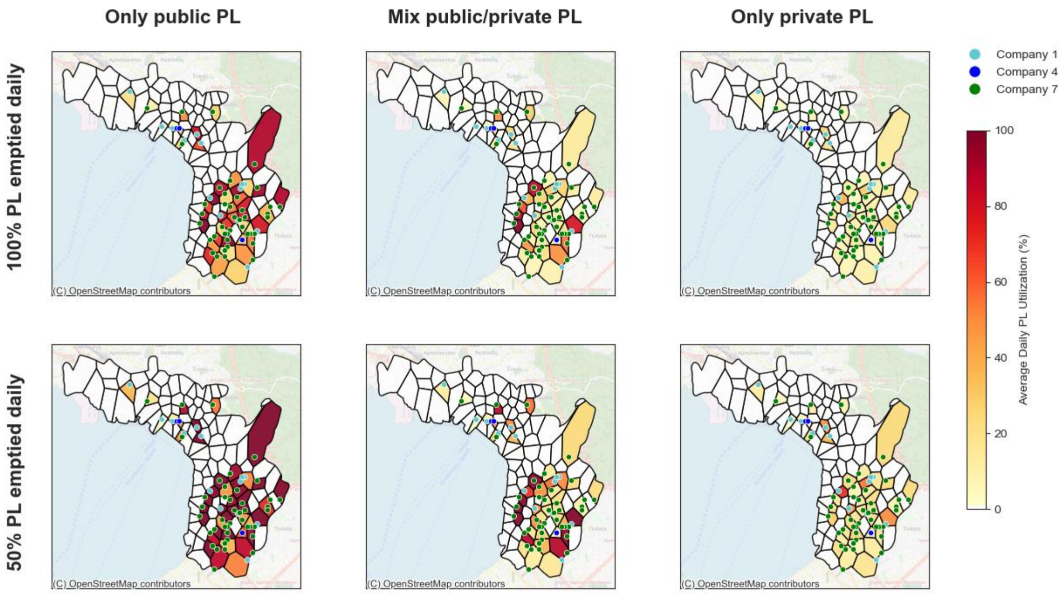

FIGURE 33 PARCEL LOCKER UTILISATION FOR INDIFFERENT CONSUMERS (5A) IN ZONES WITH PARCEL LOCKERS, PARCEL LOCKERS HAVE A CAPACITY OF 68 PARCELS (2B). RELEVANT SCENARIOS: 9, 7, 11, 10, 8, 12.

Customers with stronger preference for parcel lockers

The results of simulation scenarios with customers whose motivation and expected satisfaction patterns make them favour PLs over home deliveries show a clear jump in the PL demand (by 27%pt., from 53% to 80%). Apart from the increased PL demand, the supply side does not change significantly. Conclusions form analysing PL orders and infrastructure utilisation are qualitatively the same as the analyses described above, therefore they are not repeated here. However, the scenario visualisations are presented in Annex IV.

Parcel delivery schedules

In this section, we discuss the results of the Parcel Scheduling module. Figure 34 below presents a tour made by Company 7 in the network.

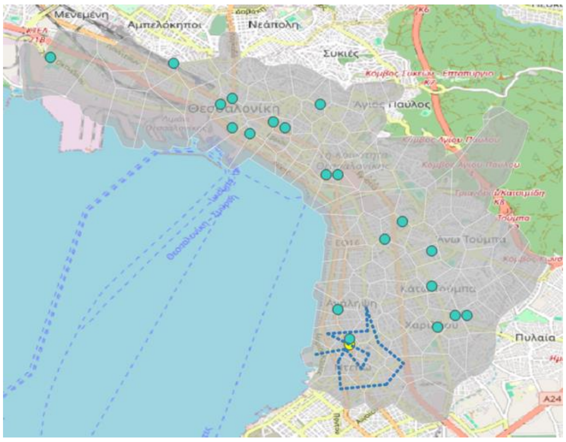

FIGURE 34 AN EXAMPLE TOUR MADE BY COMPANY 7

Considering the parcel demand and PL utilization, the tours of the companies in the network are formed. Tours are created by considering the shortest distance between O-D pairs to the company's depot location. Given that the PL facility provides an opportunity to consolidate parcels in one location, for additional parcels delivered to a PL there is no intra zonal distance calculated in the total tour distance of a company. Meanwhile, for traditional deliveries, intrazonal distances are still accounted for. This section is divided into three categories: (i) PL types where PL ownership is tested in terms of private, public, and mixed (as-is) public and private ownership of the PLs, (ii) PL utilisation where the emptiness rate of PLs is tested against fully empty (100%) and 50%, and (iii) PL capacity considering the combination of the first two categories.

i. PL Type

Table 23 shows three scenarios where different PL configurations are tested, along with a reference scenario without a PL facility in the current network.

TABLE 23 DELIVERY SCHEDULES WITH DIFFERENT PL TYPES

	Reference (no parcel locker)	PL type		
		Scenario 1 (Mix public/private)	**Scenario 3 (Public)**	**Scenario 5 (Private)**
Direct KPIs				

Vehicle kilometres (total vkm)	703.31	595.01	566.23	632.75
Company 1	128.46	82.29	61.42	101.73
Company 2	100.95	85.52	72.73	100.96
Company 3	88.39	87.31	86.39	88.40
Company 4	100.55	91.44	80.40	99.80
Company 5	95.36	94.71	93.75	95.35
Company 6	103.13	99.35	96.94	103.13
Company 7	86.46	54.36	74.61	43.38
Number of tours (total)	88	88	88	88
Number of parcels (traditional)	9021	8342	7918	8651
Number of parcels (PL)	--	679	1103	370
Efficiency KPIs				
Distance per tour (total/vkm)	7.99	6.76	6.40	7.20
Distance per parcel (total/vkm)	0.078	0.06	0.06	0.07
PL parcel per tour (total)	--	8	13	4

The direct KPIs and efficiency-related KPIs are based on the average of 10 runs executed for each scenario over 31 days. PL facilities generally reduce the total vehicle kilometres compared to a reference scenario with no PLs. The most significant reduction occurs when PL facilities are public and accessible to all courier companies. In the current network, where only Companies 1, 4, and 7 have PL facilities, Scenario 5 shows a reduction in vehicle kilometres for these companies. In contrast, Companies 3 and 5, with small market shares of 4% and 3% respectively, show minimal reduction. Efficiency KPIs indicate that Scenario 3, where all parcels are openly used by all couriers, achieves the highest efficiency, demonstrated by the lowest distance per tour and per parcel. Additionally, this scenario has the highest average number of PL parcels per tour, due to the higher volume of PL parcels. Overall, introducing PLs improves delivery efficiency by reducing travel distances, with the highest benefits seen when PLs are publicly accessible. Companies with PL facilities experience more significant reductions in vehicle kilometres, while those with smaller market shares have less impact. Scenario 3 shows the most efficient due to its open access to PLs, leading to the shortest travel distances and highest PL parcel volumes per tour.

Figure 35 shows the vehicle kilometres per courier company for Scenarios 1, 3, and 5 based on the 31-day averages and the number of parcels being delivered to the PL. The analysis presents distinct patterns for parcels being delivered across different scenarios of PL configurations: mixed public and private, all public, and all private. Scenario 3, which involves public PLs used by all courier companies, consistently shows the lowest average total distance per day. This highlights that a shared, public PL facility can effectively consolidate deliveries and minimise distance travelled. However, an interesting finding emerges for Company 7. In the as-is scenario, Company 7 has the highest number of PL facilities in the network, which are mostly operated privately. This is due to the limited capacity of PLs, which results in operational inefficiency for Company 7 when all PLs are publicly available to all couriers. In the scenario where all the PLs are private (Scenario 5), Company 7 has the biggest advantage. For the rest of the companies, Scenario 5 shows the highest tour distances since these companies do not own any PL facilities privately (Companies 2,3,5 and 6) or do not have enough capacity (Companies 1 and 4) for the PLs. These scenarios for PL type show that the decision on publicly used or fully private PL infrastructure leads to various trade-offs for the courier companies. As the Physical Internet (PI) suggests (Faugere and Montreuil, 2016) and validated by our analysis, open PL infrastructure is an enabler of reducing tour distances and affects the CO_2 emissions. However, the PL location, its capacity, how parcel demand is allocated to PLs and how the rules are determined in terms of the usage of public PLs are essential characteristics for the PL facility network design.

The emissions shown in Figure 36 further underscore these findings. The emission calculations are based on total vehicle kilometres of each individual company in the network. The emission coefficient of 121.5 CO_2 g/km is used which is the average of full and empty van in an urban area (Thoen et al., 2020). The reference scenario shows the overall highest CO2 emissions, mainly since all parcels are delivered to homes and there is no possibility of consolidation, as in the scenarios with PL. Like Figure 35, Companies 3 and 5 have the minimum difference in terms of CO2 emissions. Scenario 3 results in the lowest emissions for most companies, aligning with the observed reductions in vehicle kilometres (vkm) and improved efficiency with PLs. Companies 2, 3, 5, and 6 have the highest emissions in Scenario 5, where they do not benefit from privately owned PL facilities, thus traveling more and emitting more CO_2. On the other hand, Company 7 shows a significant decrease in emissions in Scenario 5 due to its extensive use of private PL facilities. This highlights that while public PL facilities are generally more effective in reducing emissions and travel distances in the network, the current distribution and ownership of PL facilities can significantly impact individual company performance.

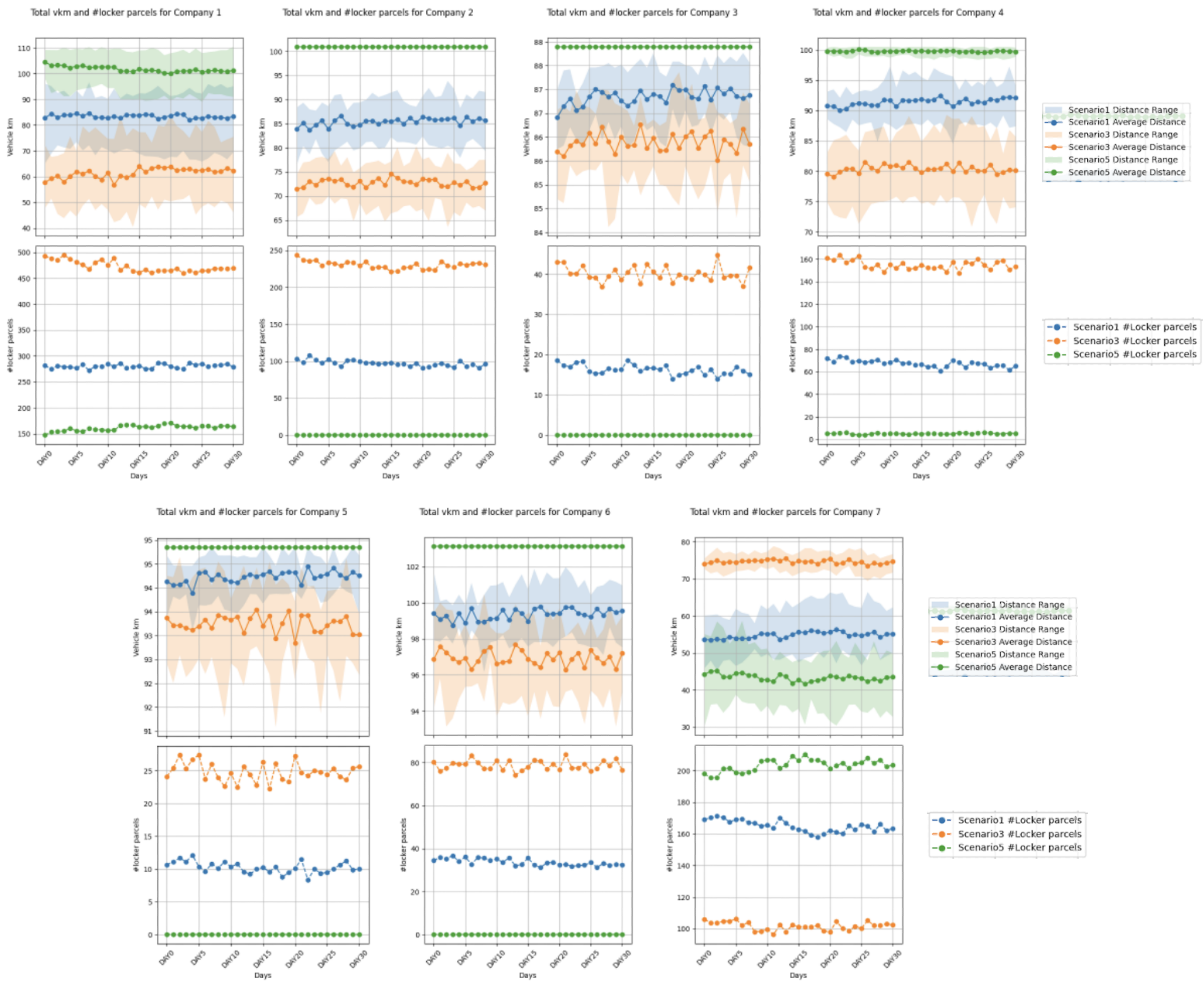

FIGURE 35 DELIVERY SCHEDULES WITH DIFFERENT PL TYPES PER COMPANY (SCENARIOS 1,3 AND 5)

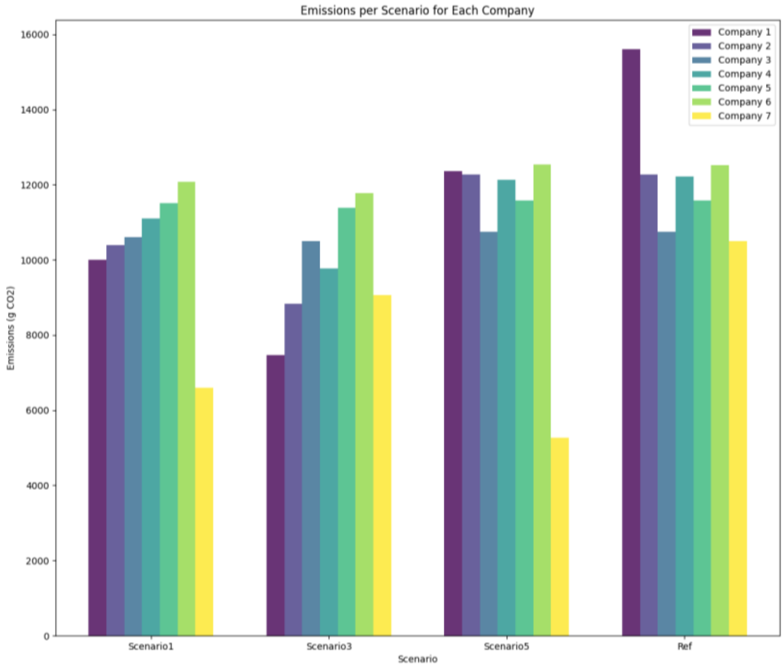

FIGURE 36 EMISSIONS WITH DIFFERENT PL TYPES (SCENARIOS 1,3,5 AND REFERENCE)

ii. PL utilisation

Table 24 shows three scenarios where different PL configurations are tested, along with a reference scenario without a PL facility in the current network. Compared to the fully available (100% emptiness) PL facility, Scenarios 2,4, and 6 show lower number of PL demand and relatively an increase on the vehicle kilometres in total.

TABLE 24 DELIVERY SCHEDULES WITH 50% PL UTILISATION

	PL Utilisation		
	Scenario 2 (Mix public/private 50% emptied)	Scenario 4 (Public 50% emptied)	Scenario 6 (Private 50% emptied)
Direct KPIs			
Vehicle kilometres (total)	616.38	609.42	642.53
Company 1	89.46	72,04	108.71
Company 2	90.88	84,49	100.96
Company 3	87.75	87,31	88.40
Company 4	95.42	89,64	99.71
Company 5	95.12	94,76	95.35
Company 6	101.35	100,29	103.13
Company 7	56,40	80,88	46.27
Number of tours (total)	88	88	88
Number of parcels (traditional)	8496	8316	8703
Number of parcels (PL)	525	705	318
Efficiency KPIs			
Distance per tour (total)	7	6.93	7.3
Distance per parcel (total)	0.070	0.070	0.071
PL parcel per tour (total)	6	8	4

Figure 35 shows the vehicle kilometres per courier company for Scenarios 2, 4, and 6, based on 31-day averages and the number of parcels being delivered to PLs. The analysis presents similarities with Scenarios 1, 3, and 5, in which the PLs are assumed to be fully emptied (100%). Scenario 2, which tests the as-is mixed PL network with a 50% emptiness rate, shows moderate vkm reduction, although the reduction is not as large as in Scenario 1. Like Scenario 3, Scenario 6 shows no change in the number of parcels being delivered for Companies 2, 3, 5, and 6, as these companies do not own a PL facility privately. A distinct pattern emerges concerning the number of parcels delivered to a PL facility and the associated average vehicle kilometres reduction. For all the companies, Scenarios 2 and 4 show that with the increase in the number of parcels delivered to a PL, the travelled distance reduces marginally. Given that the PLs in this group of scenarios are assumed to be half empty for new deliveries, the number of parcels delivered to a PL declines for all the companies, affecting the efficiency of the PL network. The analysis highlights the importance of PL availability for the overall system. Even though a delivery service like PLs provides convenience in time and location for consumers to pick up parcels, the occupancy rate of a PL box directly affects the demand for new delivery requests.

Figure 36 illustrates the CO_2 emissions for seven different companies across Scenarios 2, 4, and 6. In line with the findings in Figure 32, the private PL structure benefits Company 7 the most, while Company 1 sees the highest benefit when the PL network is fully public. This is mainly due to the high parcel demand of Company 1. Overall, CO_2 emissions per company increase because the companies lose the benefit of consolidation at a higher rate at the PL location.

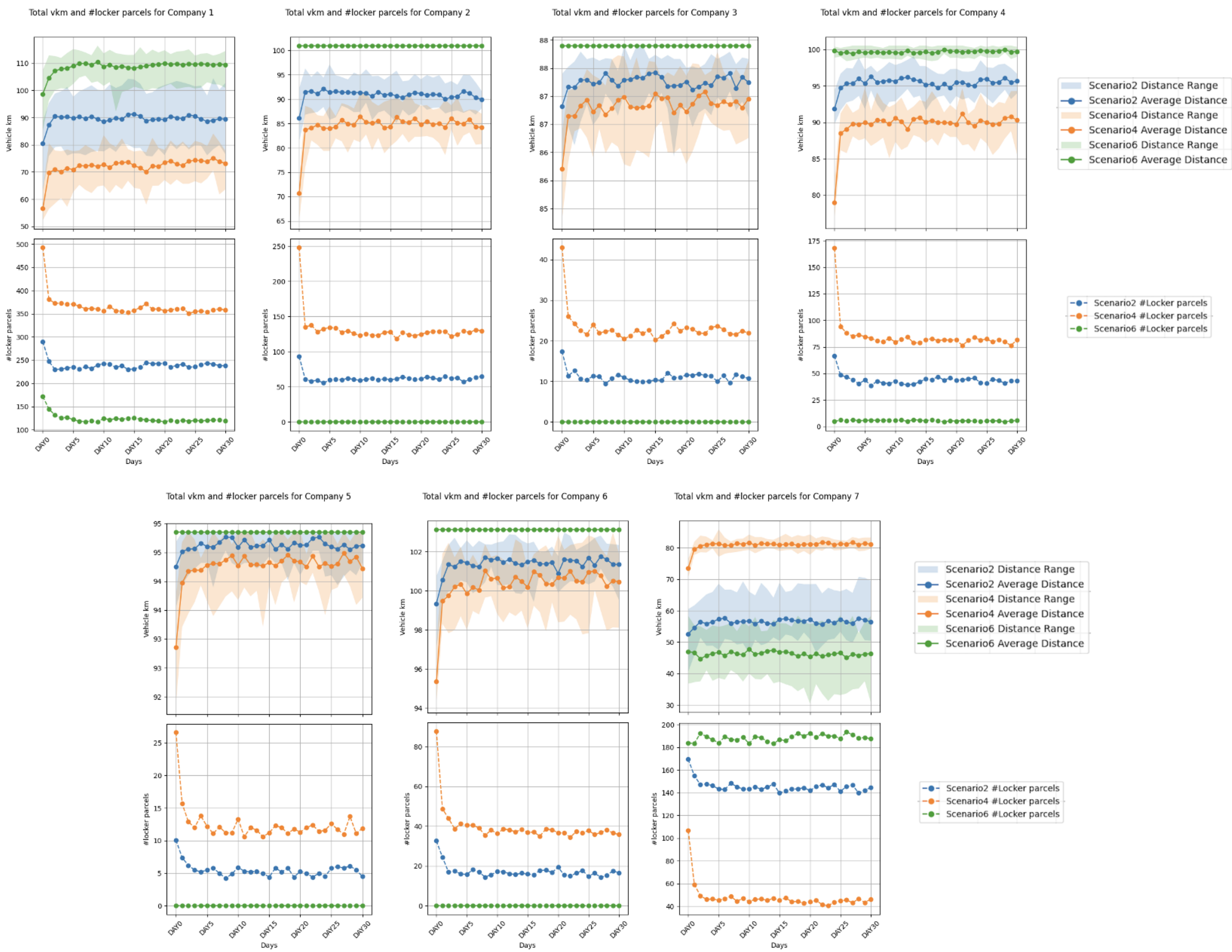

Figure 37 Delivery Schedules with (50%) PL Utilisation per Company (Scenarios 2,4 and 6)

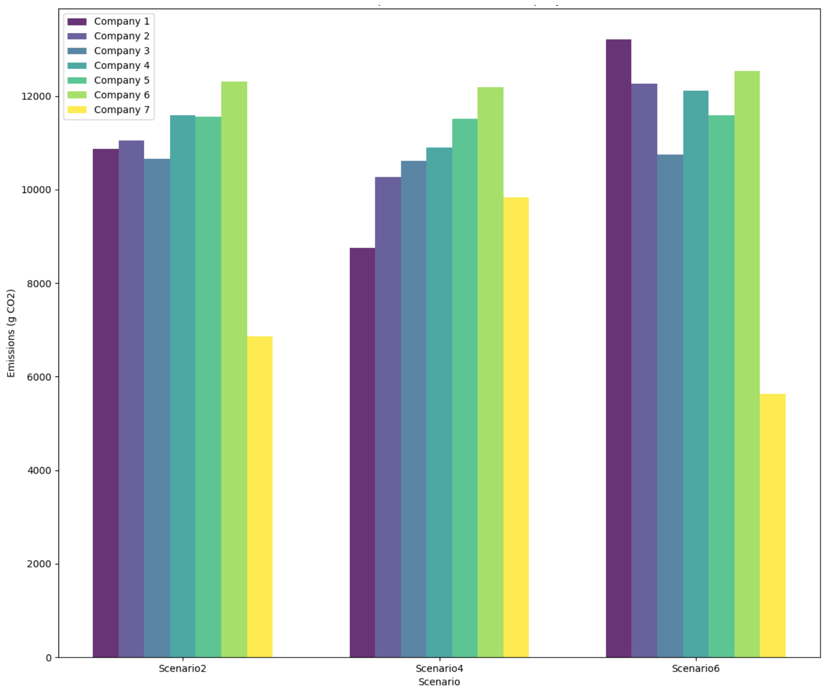

FIGURE 38 EMISSIONS WITH (50%) PL UTILISATION (SCENARIOS 2,4, AND 6)

iii. PL capacity

As the last group of scenarios, a 100% capacity increase is considered in combination with the PL type and PL utilisation cases. As seen from Table 25, Scenarios 9 and 10 have the highest PL demand, mainly due to the publicly available PL infrastructure. In Scenario 10, however, the utilisation of the PL is reduced by 50%, leading to a lower number of PL parcel demands and fewer average parcels per tour. Concerning the mix-type PL setting (tested in Scenarios 7 and 8), the total vehicle kilometres are closer to each other even though the PL utilisation is 50% in Scenario 8. Scenarios 11 and 12 show the privately owned PL network, which leads to the highest total distance travelled and the lowest number of parcels delivered at the PLs.

TABLE 25 DELIVERY SCHEDULES WITH 100% CAPACITY INCREASE

	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12
Direct KPIs						
Vehicle kilometres (total)	583.94	590.88	511.36	563.28	630.78	636.67
		77.92	53.48	63.22	100.08	100.88
Company 2	84.70	86.00	61.50	70.30	100.96	100.96
Company 3	87.04	87.29	84.67	86.44	88.40	88.40
Company 4	88.27	91.35	65.74	80.67	99.53	99.51
Company 5	94.18	94.67	91.31	93.53	95.35	95.35
Company 6	96.50	99.14	90.11	95.96	103.13	103.13
Company 7	52.04	54.50	64.55	73.15	43.32	48.44
Number of tours (total)	88	88	88	88	88	88
Number of parcels (traditional)	8227	8319	7367	7915	8653	8681
Number of parcels (PL)	793	702	1654	1106	368	340
Efficiency KPIs						
Distance per tour (total)	6.63	6.71	5.81	6.4	7.17	7.23
Distance per parcel (total)	0.064	0.066	0.062	0.062	0.070	0.070
PL parcel per tour (total)	9	8	19	13	4	4

Figure 39 shows the vehicle kilometres per courier company for Scenarios 7 to 12, based on 31-day averages and the number of parcels delivered to PLs. Since the general pattern is like the one in PL type and PL utilisation, only the average tour distances and the number of parcels delivered to PLs are represented without the range of vehicle kilometres shown in the previous scenarios for ease of representation. Overall, the results show that increasing the capacity of PLs by 100% directly affects PL demand since the demand for PL delivery exceeds the capacity in all simulation runs. Similar to the previous scenarios, the capacity increase does not affect Companies 4 and 5 due to insufficient parcel demand. Scenarios 7 (mixed PL ownership with 100% emptiness) and 8 (mixed PL ownership with 50% emptiness) show that only for Company 1, even half-empty PLs bring benefits in terms of distance travelled since Company 1 has the most significant parcel demand combined with PLs and home deliveries. This leads to an advantage in leveraging PLs to a higher extent. Like Scenarios 3 and 4, the public use of PLs (in Scenarios 9 and 10) benefits most courier companies regarding average tour distances. Considering the privately owned PLs with double capacity in Scenarios 11 and 12, while the indicators worsen for Company 1, Company 7 has the most significant advantage due to its already existing locker infrastructure. Interestingly, Company 4, which has its own PL facility in the network, does not benefit as much as Companies 1 and 7 mainly because of the lower number of PLs that Company 4 has in the network. This means that public and mixed PL types are also more beneficial for companies with a less dense PL network.

Figure 40 illustrates the CO2 emissions for seven different companies across Scenarios 2, 4, and 6. In line with the findings in Figure 36 and Figure 38, the lower vehicle kilometres result in lower CO_2 emission.

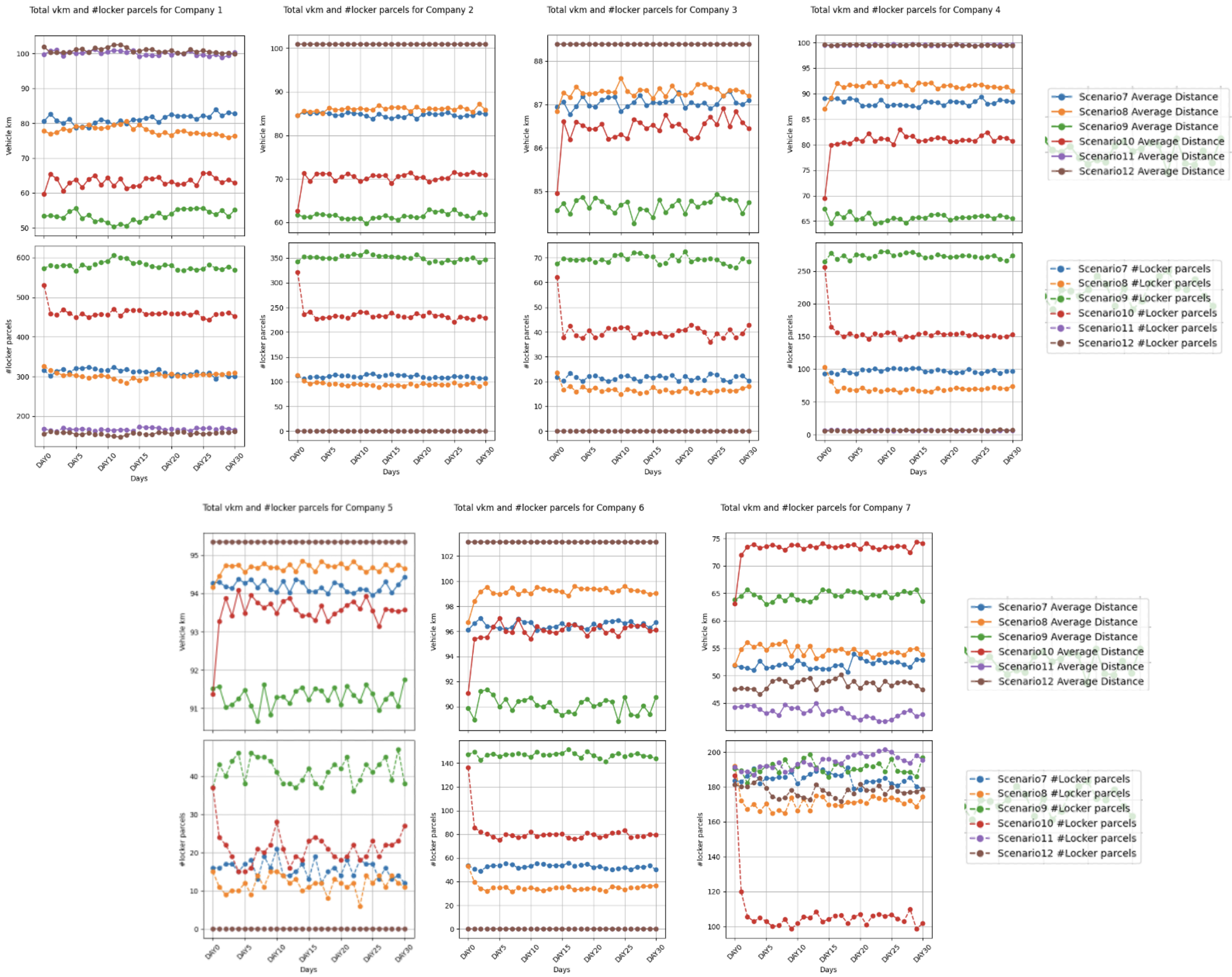

FIGURE 39 DELIVERY SCHEDULES WITH CAPACITY INCREASE (SCENARIOS 7-12)

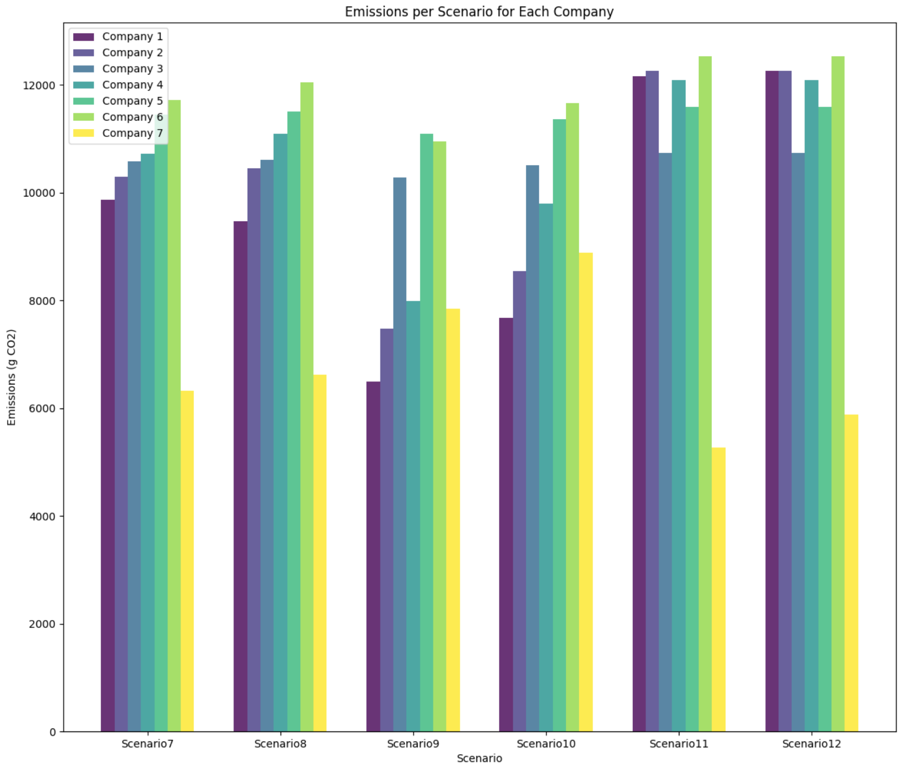

FIGURE 40 EMISSIONS WITH CAPACITY INCREASE (SCENARIOS 7-12)

Delivery schedules of consumers with a slight preference towards PLs do not lead to marginal changes and can be found in Annex V.

7.2. Autonomous Delivery Vehicle Service (Helsinki LL)

7.2.1. Simulations

Simulations of the URBANE ABM are carried out through implementing what-if scenarios in a DT of Helsinki with the population scaled 1:10. A what-if scenario is defined as a combination of 5 parameter values communicated to the model at the initialization. Table 26, summarizing the ABM simulation parameters and their settings, is followed by a description of parameter values. Next, a table of the simulated scenarios is provided in Table 28.

TABLE 26 ABM SIMULATION PARAMETERS AND THEIR SETTINGS

Parameter	Settings
1. ADV Network	A. 1 ADV belonging to 1 company (DBS), with defined delivery locations
2. ADV capacity	B. 15
	C. 30
	D. 300

3. Customer arrival rate	1. 5 customers/minute
	2. 1 customer/minute
4. Service rate	A. 2 customers/ minute
5. Consumer satisfactions	A. Indifferent consumers

Parameter descriptions:

1. ADV network

Changes to the ADV network allow for testing different ADV configurations related to courier companies. The parameter currently has a single baseline setting used in all simulation scenarios, the ***A. As is***, described in the form of a .csv file (*ADV_capacity.csv*), which constitutes the content of the Fulfilment data input. In the ***As is*** setting, Helsinki has 1 ADV belonging to 1 company. The ADV travels to 5 different locations, each in a different city zone, and is available there for a maximum of 60 minutes, so that customers can pick up the ordered parcels. To change this parameter to a different setting, a new .csv file should be provided as input. Additional settings can reflect alternative states of affairs. For example, a what-if with a new service provider, Company 2, entering the Helsinki market and owning another ADV or a what-if with the existing provider expanding their infrastructure by adding an additional ADV.

TABLE 27 TIME AVAILABILITY

Zone	Maximum time availability
Helsinki Keskusta - Etu-Töölö	60 minutes
Eira - Hernesaari	60 minutes
Punavuori	60 minutes
Jätkäsaari	60 minutes
Kamppi - Ruoholahti	60 minutes

2. ADV capacity

Changes of the capacity parameter enable simulating various capacities of the ADV. The baseline capacity is defined as 15 parcels (***A. 15***). This means that the ADV can deliver 15 parcels per delivery location (zone). The baseline setting is described in the form of a .csv file (*ADV_capacity.csv*), which constitutes the content of the Fulfilment data input. Alternatively, the simulation doubles the capacity (***B. 30***) or sets the capacity to unlimited (**C. unlimited**). Additional settings can reflect what-ifs of a different uniform capacity value or capacities varying by an ADV (or ADV type).

3. Customer arrival rate

Changes of the customer arrival rate alternate the number of customers that will arrive to collection site every minute, starting at the time when the ADV is available. The baseline scenario (***A. 5/minute***) assumes that all customers who ordered via the ADV start arriving at the collection site as soon as the ADV is available and arrive at an average pace of 5 customers per minute. The alternative setting reflects an average arrival rate of 1 customer per minute (***B. 1/minute***).

4. **Service rate**

Altering the service rate influences the time of serving a single customer. The baseline scenario (**A. 2 customers/minute**) assumes that each customer will be served within an average of 30 seconds. Additional settings can reflect what-ifs of a lower temporal efficiency.

5. **Customer satisfactions**

Changes of the consumer satisfactions parameter reflect changes in the structure of motivations and fulfilment type satisfactions among the socio-demographic segments of the urban population. Altering this setting requires modification to the content of the Consumer Motives Data. In the ***A. Indifferent consumers setting***, the motive importances and choice satisfactions of all socio-demographic customer segments are assumed indifferent between home delivery and ADV delivery. Importances of motives and choice satisfactions assumed normally distributed around a neutral mean.

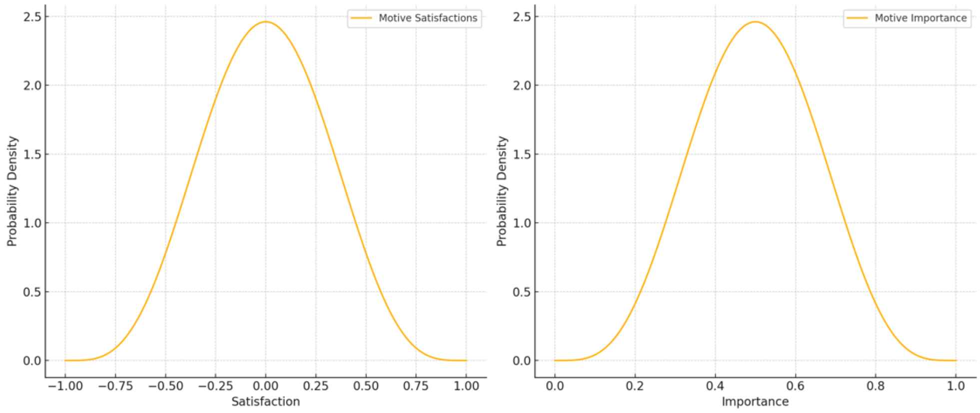

FIGURE 41 DISTRIBUTION OF CUSTOMER MOTIVE SATISFACTIONS AND IMPORTANCES IN THE HELSINKI LL ABM

Each of the 6 simulated scenarios is a unique combination of parameter settings. For example, scenario 1, which serves as a reference baseline scenario, is a combination of the first setting of all parameters (i.e., 1A, 2A, 3A, 4A, 5A) and represents a situation with the status quo of the ADV network: one available ADV with defined delivery locations (1A) and a capacity per location of 15 parcels (2A). The customer arrival rate is set to 5 per minute (3A), the ADV has a service rate of 5 customers per minute (4A), and the population is indifferent between home delivery and ADV delivery (5A). Table 28 lists the simulated scenarios.

TABLE 28 SIMULATION SCENARIOS OF HELSINKI ABM.

Scenario	1 ADV Network	2 ADV Capacity	3 Customer arrival rate	4. Service rate	5 Choice Satisfaction
Scenario 1	1A	2A	3A	4A	5A
Scenario 2	1A	2A	3B	4A	5A
Scenario 3	1A	2B	3A	4A	5A
Scenario 4	1A	2B	3B	4A	5A
Scenario 5	1A	2C	3A	4A	5A
Scenario 6	1A	2C	3B	4A	5A

7.2.2. Results

Demand generation

The parcel demand in Helsinki was generated following the same procedure applied to Thessaloniki and described in Section 7.1.2. Given the data gathered from the Helsinki LL, we have generated the demand per household in the study area. The main parameters are provided in Table.

TABLE 29 MAIN DEMAND PARAMETERS FOR THE HELSINKI LL

Number of parcels (year)	40703
Number of inhabitants	31418
Number of working days	250
Parcel success rate	0.85
Income per zone	3.008e-05
Employment per zone	0.0000

Due to the lack of data on the zonal and network level information of the LL, we have only used the average demand data provided by our project partner, DB Schenker, without including any other couriers in the network. Since our ABM is designed to be generalizable to other use cases, we have used the same approach as employed in the Thessaloniki LL. However, the limited data leads to a smaller scale application for the Helsinki LL.

PARCELS_PER_HH data is provided by our project partner, DB Schenker, and represents the average demand. Additionally, Helsinki LL provided information on the household structure for the use case area. Like the Thessaloniki LL, we considered the number of working days and parcel success rate as 250 and 0.85, respectively. Lastly, the parameter "INCOME_PER_ZONE," showing the regression coefficient, is calculated as 3.008e-05 and was established via a linear regression model. The specifications of the regression model are represented in Annex II: Input Data Preparation for MASS-GT for Helsinki LL. The parameter "PARCELS_PER_EMPL," representing the number of parcels based on employment characteristics, is set at 0.000 and is included for generalization purposes due to the absence of data. The network, including the parcel node (depot location) of DB Schenker is presented in Figure 42.

FIGURE 42 ZONES OF THE HELSINKI LL

Given the parameters in The parcel demand in Helsinki was generated following the same procedure applied to Thessaloniki and described in Section 7.1.2. Given the data gathered from the Helsinki LL, we have generated the demand per household in the study area. The main parameters are provided in Table.

Table 29 and the network data, the Parcel Demand module generated 220 parcels for the study area (Figure 42 Zones of the Helsinki LL). The distribution of the parcels is presented in Figure 43.

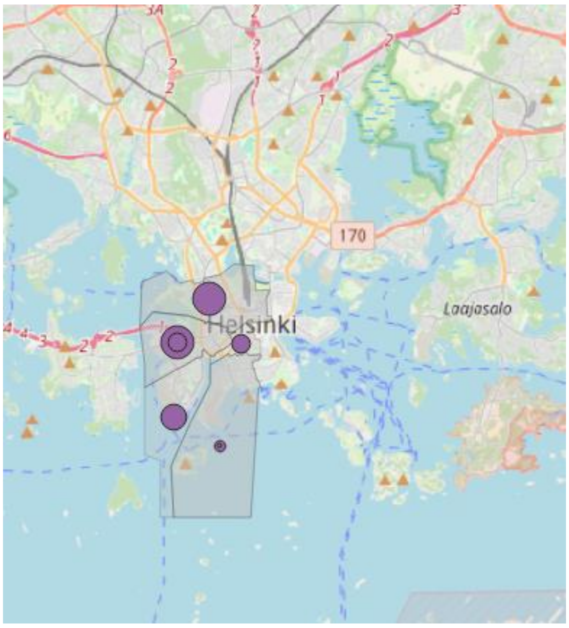

FIGURE 43 DEMAND DISTRIBUTION OF THE HELSINKI LL

ADV demand

Based on their motive structure, HUMAT agents in the ABM choose their preferred fulfilment type. In the indifferent customer preference scenarios (scenario settings 5A), on average 50% of agents would like to have their parcel delivered via an ADV. This makes for an average daily ADV demand of 110 parcels (Figure 45). As the demand for ADV is independent of other scenario parameter settings, it fluctuates only marginally over the course of one simulation. The fluctuation is a result of minor changes in consumer perceptions of home deliveries and ADV originating in social network information exchanges about the two fulfilment types.

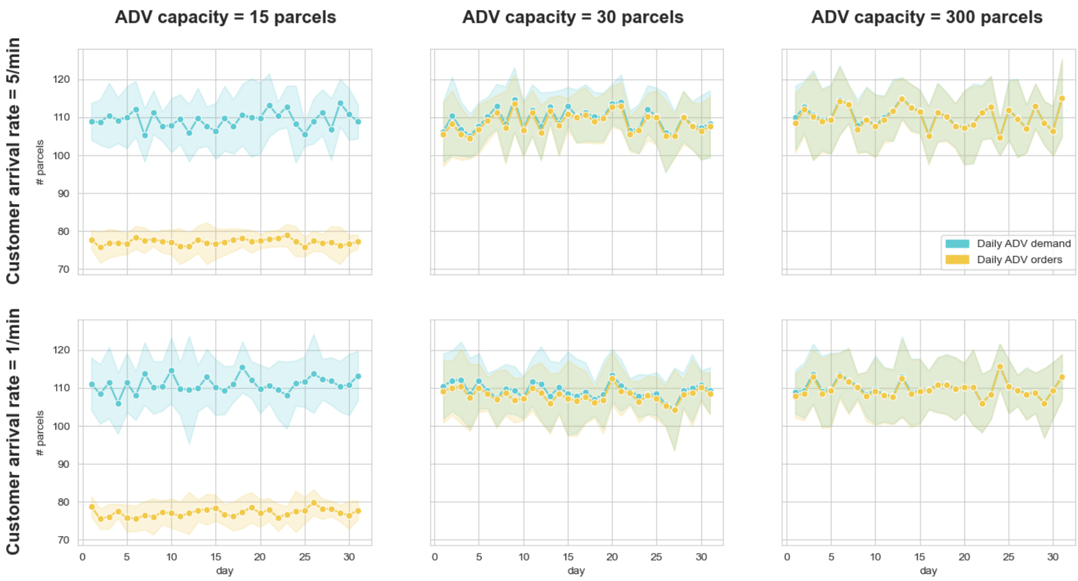

FIGURE 43 ADV DEMAND AND ADV ORDERS FOR INDIFFERENT CONSUMERS (5A) BY ADV CAPACITY AND CUSTOMER ARRIVAL RATE. RELEVANT SCENARIOS: 1 (TOP LEFT), 3, 5 (TOP RIGHT), 2 (BOTTOM LEFT), 4, 6 (BOTTOM RIGHT).

Regardless of customer preferences, parcels are ultimately delivered via a fulfilment type that is available at a given time step. As a result, HUMAT agents only get to use ADV if it has not yet reached its full parcel capacity. As expected, the parcel capacity of the ADV determines if the ADV supply can sufficiently respond to customer demand. In scenario settings that limit ADV parcel capacity to 15 parcels per zone and customers indifferent with respect to preferred fulfilment type, the ADV demand exceeds supply. Doubling the ADV capacity or increasing it indefinitely results in meeting the customer demand. Customer arrival rate does not impact the number of orders sent daily to an ADV; however, it does influence the number of parcels that are effectively delivered via the ADV (see Figure 47).

ADV performance

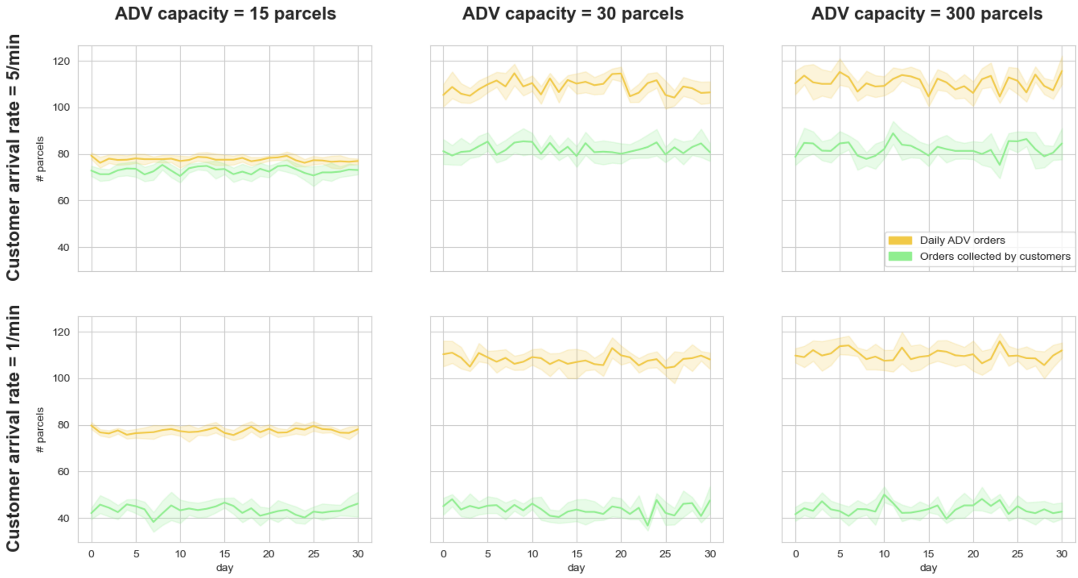

FIGURE 44 AVERAGE PARCELS DELIVERED BY ADV.

RELEVANT SCENARIOS: 1 (TOP LEFT), 3, 5 (TOP RIGHT), 2 (BOTTOM LEFT), 4, 6 (BOTTOM RIGHT).

Fig. 44 shows the performance of an ADV over 31 days by comparing the number of parcels to deliver and parcels delivered under various capacity and customer arrival rates. The arrival rates of customers per minute, shows that higher ADV capacities (30 and 300 parcels) do not significantly improve delivery rate. The main reason for this outcome is due to the time window constraints (i.e., the period within which the ADV must visit a location, e.g. between 11:30 and 12:45) and the capacity constraints of the ADV. The analysis shows that increasing ADV capacity alone does not ensure higher delivery efficiency, especially under higher demand scenarios. Increasing the width of the time windows as well as the ADV's waiting time at each delivery location will improve the delivery rate. This however will result in an increase in the ADV's total operating time. 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.

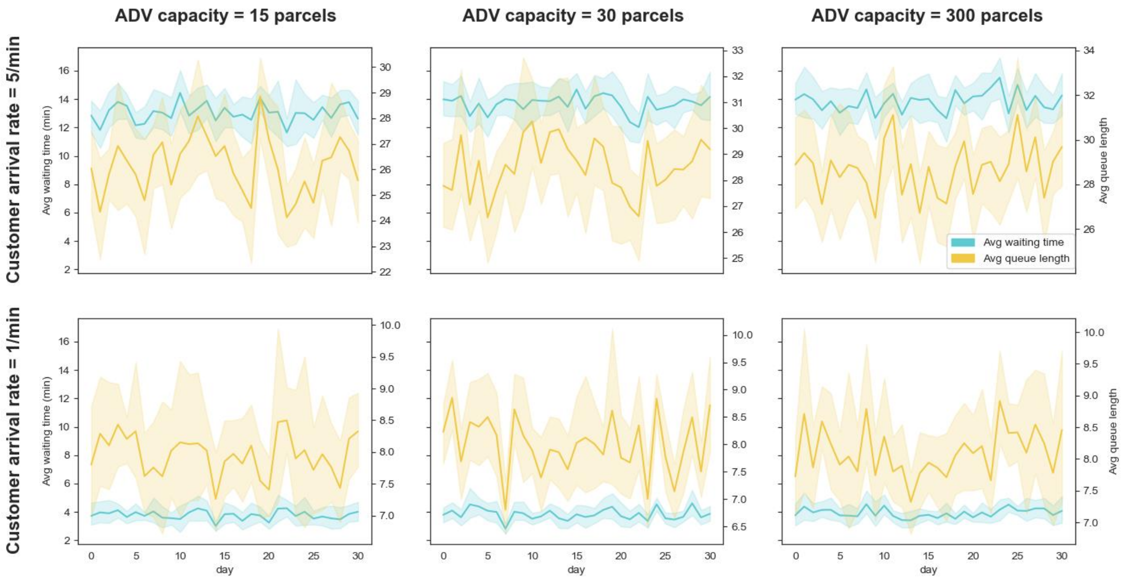

FIGURE 45 AVERAGE WAITING TIME AND QUEUE LENGTH WITH ADV DELIVERY

Figure 47 shows the average waiting time and average queue length over a 31-day period of ADV delivery. As expected, when the customer arrivals are higher (5 customer per minute), the average waiting time and average queue length become higher since there are more customers picking up their parcels from the ADV, creating higher waiting times and longer queue.

TABLE 30 AVERAGE CO2 EMISSION PER PARCEL BY ADV

Scenario	Average CO_2 emission per delivered parcel
1	67.80
2	113.71
3	60.18
4	112.75
5	60.15
6	112.32

Table 30 shows that Scenarios 3 and 5 have the lowest CO_2 emission rate per parcel delivered. Even though the capacity is 10 times higher in Scenario 5, the difference in capacity does not result in a significant CO_2 reduction, mainly because the *total* CO_2 emissions rate is a function of the number of delivery locations visited. Since the customer arrival rate is lower in Scenarios 2, 4, and 6, the number of parcels delivered is also lower, leading to higher CO_2 emissions per parcel.

8 Discussion

This deliverable presents several significant innovations that contribute to the broader objectives of the URBANE project. The innovations that are developed in this study are: (1) a generic functional architecture of the integrated modelling framework that is more straightforward to calibrate for new cases, (2) the calibrated agent-based models which are reusable for similar cases of other Living Labs.

8.1 Integration and Interoperability of Models

Integrating the HUMAT and MASS-GT simulation models made it necessary to re-implement HUMAT (previously written in NetLogo) in Python. This decision was primarily influenced by the project's requirement to merge the distinct functionalities of both models into a cohesive simulation framework, facilitating streamlined interactions, data exchange processes and flexibility for further use cases. Using the Mesa ABM framework within the Python ecosystem was instrumental, as it enriched Python with specialized functionalities tailored for ABM development while offering a breadth of Python libraries. Translating HUMAT from NetLogo to Python posed several challenges. NetLogo's model is structured around a collection of procedures, including a setup phase that defines agent parameters and their environment and a main execution loop that drives the model's processes for a set number of time steps. This procedural approach contrasts with Python's object-oriented (OO) paradigm, which focuses on defining classes and objects that interact with each other. Adapting the procedural logic of NetLogo into the object-oriented framework of Python required a thoughtful reorganisation of the model's structure. We had to devise new ways to initialise the simulation environment and manage the execution flow to replicate the behaviour of the original NetLogo model within Python's OO context.

The integration of the HUMAT architecture has resulted in developments at the aggregation level of MASS-GT modules. For this purpose, a synthetic population is generated for the use cases, and the linkage between the MASS-GT zoning system and the population is utilised. By employing a proportional distribution of households in a zone and corresponding sociodemographic characteristics, we are able to effectively distribute these households into the MASS-GT zoning system. For the Thessaloniki and Helsinki use cases, we have generated synthetic population based on the EUROSTAT population sample. This enabled us to develop a modular population synthesiser for use in other cities.

Integrating the HUMAT and MASS-GT models into a single Python framework presented unique challenges, particularly in harmonising the different agent structures and simulation dynamics approaches. The main class of each LL use case implementation initialises various use case-specific input data and addresses the inherent complexities of merging two distinct models. It was designed to ensure that the individual agents in HUMAT could interact with the household entities in MASS-GT.

The model class played a critical role in synchronising time steps and scheduling, a task made difficult by the differing temporal resolutions of the two models. We developed methods that could handle the discrete time steps of HUMAT while simultaneously catering to the aggregate time scales used in MASS-GT. This involved creating a scheduler that could coordinate actions across both models, allowing for a transition between individual and collective agent behaviours and ensuring data consistency throughout the simulation.

Communication between the models, regarding agent actions and interactions, required a careful orchestration of data exchange. The agent class was equipped with mechanisms to translate the actions of individual HUMAT agents into a format that could be understood and acted upon within the MASS-GT model's household structures, and vice versa. Functions and methods were designed to be reusable and adaptable to different LL use case settings.

8.2 Impact of Social Networks

By integrating social networks into the simulation of LMD services, the model captures how consumer preferences can be influenced by their social networks. As shown in Table 6, for instance, in scenarios where parcel lockers are preferred over home delivery, the model can simulate how peer influence within certain demographic groups drive the adoption of parcel locker services. In a similar setting, by simulating consumer satisfactions in terms of their motives (e.g., rime and low environmental impact), consumer behaviour can significantly impact the choice of the logistics service as detailed in sections 7.1 and 7.2.

The integration of calibrated data for each use case allows for the modelling of more realistic scenarios, where consumer satisfaction and preferences are not homogenous but vary according to social-demographic segments. This heterogeneity, driven by homophily dimensions such as age groups and education levels, leads to a better understanding of how different groups might react to changes in choice of delivery methods such as PLs and ADVs.

Our simulation results show that accounting for the changes in social behaviour directly affect the choice of the delivery method such as PL. This, in turn, influences how logistical processes need to adapt dynamically to changing consumer preferences. For instance, in a simulation scenario where PLs are preferred over home delivery (in Section 7.1) leads to an increase in the choice for parcel lockers if the capacity for PLs allows. The model can predict the impact of these changes and suggest adjustments to the logistical network and delivery schedules. This demonstrates that considering social changes in the LMD system allows for more realistic logistical planning.

8.3 Calibrated Agent-based Models

The integrated modelling framework was calibrated and validated using data from the Thessaloniki and Helsinki Living Labs (LLs), enabling the modelling and simulation of the PL and the ADV services relevant to the LMD context of the URBANE project.

The PL service (Thessaloniki LL) focuses on implementing PLs strategically located within urban areas to streamline last-mile deliveries. The simulation results indicate that PLs can significantly enhance delivery efficiency by reducing the number of trips required, thereby lowering operational costs and carbon emissions. However, the success of this service depends heavily on consumer acceptance, with some consumers preferring the convenience of home delivery while others appreciate the flexibility and security of using PLs. Overall, the service is particularly beneficial in densely populated areas where it can effectively mitigate delivery traffic and its associated environmental impact.

The ADV service (Helsinki LL) models the deployment of autonomous vehicles for direct parcel deliveries to consumers. This service is designed to optimize delivery routes and schedules, thereby minimizing travel distances and improving overall delivery efficiency. The simulation suggests that while increasing the capacity of ADVs can reduce the number of trips, this benefit is most effective when coupled with optimised delivery schedules. The environmental impact of ADVs is also significant, with the potential for substantial reductions in CO2 emissions in regions where renewable energy sources are prevalent. However, in areas dependent on fossil fuels, the environmental benefits are less pronounced.

Having said, we should note that, we encountered several challenges during the calibration and validation of these ABMs. Due to the unavailability of certain empirical data, particularly for the ADV service (Helsinki LL), the models currently rely on minimum amount of data, which may affect the accuracy of predictions. The absence of detailed social network data for Thessaloniki also posed difficulties, leading to the use of generalised assumptions for social network topologies, which may not fully capture the local social dynamics.

The calibration process was further complicated by the need to normalise and adjust data inputs, particularly in the HUMAT model, to reflect real-world distributions as closely as possible. The use of beta distributions to simulate consumer motives and behaviours was a novel approach, yet it required extensive parameter tuning to align with empirical observations. This iterative process highlighted the importance of having robust, high-quality data for model calibration, which remains a priority for future work.

8.4 Integration of Services into URBANE's Digital Twin (DT) Platform

A crucial aspect of the URBANE project is the integration of the developed simulation models into the DT platform. The DT platform serves as a dynamic, real-time simulation environment that replicates the urban logistics ecosystem, allowing for continuous monitoring, simulation, and optimization of LMD operations. The integration of these services into the DT platform enables stakeholders to visualise and analyse the impact of these innovations in a virtual urban environment before implementation in the real world.

For the PL service (Thessaloniki LL), the DT platform offers a means to dynamically simulate and optimise the placement of lockers, evaluate their usage patterns, and assess their impact on delivery efficiency and traffic congestion. This integration allows for adjustments based on actual usage data, ensuring that the locker network remains responsive to changing consumer behaviour and urban conditions.

Similarly, the ADV Service benefits from integration into the DT platform by enabling route optimisation and energy consumption monitoring. The platform can simulate various scenarios, such as changes in traffic conditions or energy supply fluctuations and adjust the ADV operations accordingly to maintain efficiency and reduce environmental impact. The DT platform also provides a comprehensive view of the interactions between different urban logistics components, allowing for a more holistic approach to managing last-mile deliveries.

Overall, the integration of these services into the DT platform enhances the URBANE project's ability to deliver sustainable, efficient, consumer-friendly and transferable urban logistics solutions. This integration not only improves the immediate deployment and operation of these services but also provides a scalable and adaptable framework that can be applied to other cities and urban contexts within the project's broader scope.

8.5 Implications for Urban Logistics

The models developed under this deliverable offer significant insights into the complexities of LMD systems in urban environments. By simulating various scenarios and testing different logistic innovations, the models provide a powerful tool for urban planners and policymakers to explore the potential impacts of new LMD strategies. For instance, the simulation results from the Thessaloniki LL demonstrated the effectiveness of PLs in reducing delivery times and emissions, though the success of such innovations is heavily dependent on consumer acceptance and the configuration of the locker network.

Similarly, the simulations for the Helsinki LL's ADV service revealed the nuanced trade-offs between delivery efficiency and environmental impact. While increasing ADV capacity did not significantly improve delivery efficiency under certain scenarios, it highlighted the importance of optimizing delivery schedules and time windows to maximize the utility of such technologies.

These findings underscore the need for a holistic approach to urban logistics, where technological innovations must be carefully evaluated within the context of local infrastructure, consumer behaviour, and environmental goals. The agent-based models developed here serve as a crucial step toward creating more sustainable and efficient urban logistics systems, though their effectiveness will ultimately depend on continued data integration and model refinement.

8.6 Broader Impacts and Future Directions

The broader impact of this deliverable extends beyond the specific case studies of Thessaloniki LL and Helsinki LL. The modular nature of the developed models makes them adaptable to other urban contexts, allowing for the replication of the studies in different cities with varying logistical challenges. This flexibility is vital for the scalability of the URBANE project's objectives, as it enables the application of these models in other LLs and contributes to the development of a replicable framework for urban logistics innovation.

9 Strategic Recommendations to Stakeholders

Strategic recommendations for stakeholders at EU level, including the Committee of Regions and the European Commission, are as follows:

- Identify and support local solutions: EU actors, including the Committee of Regions, should ensure that measures seeking to reduce CO2 emission move beyond recognition of local concerns about national solutions.
- Those measures should instead seek local solutions for those problems, supporting cities and regions in meeting their own needs to facilitate LMD services and reduce administrative barriers.
- Provide opportunities to promote cities to talent: EU actors, most notably the European Commission, should provide opportunities for cities and regions to showcase their approach and highlight their needs in improving LMD systems.
- Support idea generation and sharing initiatives: EU actors, including the Committee of Regions, should convene sandpit initiatives, in close cooperation with municipalities, carriers and civil society, to support idea generation.

Strategic recommendations for stakeholders at the European, national, regional and local level:

- Improve cooperation and multi-level governance: Collaboration and governance mechanisms should be enhanced across various levels of government and stakeholders involved in LMD services to foster a more integrated and cohesive approach to addressing the challenges and opportunities in urban logistics. Towards a connected PI network, improving cooperation involves facilitating better communication, coordination, and sharing of best practices among EU, national, regional, and local authorities, as well as private stakeholders like logistics companies and technology providers. This holistic approach ensures that policies and initiatives are more aligned, efficient, and effective in meeting the collective goal of sustainable and resilient urban logistics systems.
- Support the development of infrastructure that fulfils the growing demand for innovative delivery options: The results prove that consumer satisfaction and preferences directly influence the choice of innovative delivery services, mainly influenced by the availability of the service provided to consumers. Therefore, it is essential to have mechanism regulating the use of openly available infrastructure.
- Promote the development of an open and collaborative PI network: Our analysis shows that the public use of existing infrastructure does not seem to affect local actors equally. Creating an open PI network can be efficient at both the system and individual levels if the stakeholders do not promote these developments and the use of this open infrastructure is clearly defined. This could also help build trust in the open network among individual actors such as LSPs and ADV service providers.

Strategic recommendation for stakeholders at the national level, in collaboration with regional and local actors:

- Greater role for cities and regions in improving LMD services: Cities and regions should take a more significant role in the development, implementation, and management of LMD solutions. The unique characteristics of urban and regional contexts mean that local authorities are best placed to understand the specific challenges and opportunities within their territories. By granting cities and regions greater autonomy and resources, they can innovate and implement tailored solutions that address their unique logistics, environmental, and social challenges. This includes the development of infrastructure, regulatory frameworks, and partnerships that support sustainable LMD practices. Empowering local authorities in this way encourages more localised, efficient, and adaptable LMD systems, contributing to the overall goal of reducing congestion, pollution, and enhancing urban liveability.

10 Conclusions

This document has presented a comprehensive and modular modelling framework and set of calibrated ABMs designed to advance the objectives of the URBANE project, particularly within Task 3.4. The journey from the modelling framework to practical applications has not been finished yet. The strides made so far demonstrate significant progress in urban logistics simulation and the potential for scalable impact.

The modelling framework (Section 5) and ABMs developed (Section 6) under Deliverable D3.2 have been pivotal in capturing the intricacies of LMD systems and the social dynamics of living labs. This has facilitated a nuanced understanding of urban logistics and the behavioural patterns of various stakeholders. Moreover, the deliverable has provided a robust basis for in-silico experimentation, enabling the exploration of counterfactual scenarios and the assessment of potential innovation uptakes within urban environments.

The integration of the HUMAT and MASS-GT models, as detailed in this deliverable, represents a significant milestone for the URBANE project. This symbiosis of models has yielded a powerful promising tool for analysing the diffusion of innovations and the acceptance of new logistics strategies by various stakeholders. As we reflect on the progress made, these models are not merely academic exercises but are intended to serve as instruments for strategic decision-making and policy formulation (see Section 8). However, this does not mean that they do not have limitations. Due to the unavailability of data, the current models work on the reduced data, which would decrease the accuracy of model predictions.

The results show that the biggest challenge towards implementing the PI concept lies with meeting consumer satisfaction and the capacity constraints of the delivery method provided (e.g., PLs, ADVs). Moreover, the simulations show that open and shared PL infrastructure enables reducing tour distances and directly affects CO_2 emissions. However, the PL location, its capacity, how parcel demand is allocated to PLs and how the rules are determined regarding the shared infrastructure of public PLs are essential characteristics for the PL facility network design.

As the project moves forward, the models and findings presented here (Section 7) will serve as foundational elements for LMD logistics. They will inform the development of policy recommendations, the design of sustainable urban logistics strategies, and ultimately contribute to the creation of more liveable and efficient urban spaces.

Looking ahead, the true value of the modelling framework and ABMs developed in this deliverable will be realized through their application in additional living labs, such as those planned in Barcelona and Karlsruhe. The ongoing engagement with stakeholders, particularly through these Lighthouse Living Labs, will be crucial in refining the models, ensuring they are grounded in real-world logistics challenges, and ultimately driving meaningful change in urban logistics systems.

In summary, while significant progress has been made, this deliverable represents just the beginning of a broader effort to revolutionize urban logistics through innovative modelling techniques. The work laid out here provides a solid foundation for future research, development, and practical application, all of which will contribute to creating more sustainable, efficient, and liveable urban spaces.

11 Future Work

The work carried out in this deliverable establishes a robust foundation for modelling LMD systems using an integrated agent-based modelling (ABM) framework. However, several avenues for future research and development can further enhance the effectiveness and applicability of the framework.

Expansion to Additional Living Labs: While the current framework has been successfully applied to Thessaloniki and Helsinki, there is a need to extend the application to other urban contexts. Expanding to additional living labs in different geographic and socio-economic settings will help in validating the generalizability of the models and refine them based on diverse urban logistics scenarios.

Integration with Real-Time Data: The integration of real-time data into the ABM framework could significantly enhance the predictive accuracy and adaptability of the models. Future work should focus on developing mechanisms to incorporate live data feeds, such as real-time traffic conditions, delivery vehicle statuses, and dynamic consumer preferences, into the simulation models.

Advanced Calibration Techniques: While the current models have been calibrated using available data, future efforts could explore advanced calibration techniques, such as machine learning algorithms, to automatically adjust model parameters. This approach could improve the precision of simulations and reduce the need for manual adjustments.

Incorporation of Environmental and Economic Metrics: Future work could expand the modelling framework to include comprehensive environmental and economic impact assessments. This could involve integrating modules that simulate the carbon footprint of different delivery methods, and the economic costs associated with various LMD strategies, thereby providing stakeholders with a more holistic understanding of the trade-offs involved.

Exploration of Novel Delivery Methods: As urban logistics continue to evolve, there is a need to explore and model the impact of emerging delivery methods, such as drone-based delivery, electric cargo bikes, and shared delivery services. Future research should focus on developing models that can simulate these innovative delivery systems and assess their feasibility and impact in urban environments.

User-Centric Enhancements: Further research is needed to better understand and model consumer behaviour in response to different LMD options. This includes the incorporation of more detailed socio-demographic and psychographic data into the ABM framework, as well as the development of user-friendly interfaces that allow consumers to interact with the models, thereby enhancing stakeholder engagement.

Longitudinal Studies: To fully understand the long-term implications of various LMD strategies, it is essential to conduct longitudinal studies that track changes in consumer behaviour, environmental impact, and logistical efficiency over time. Future work should focus on setting up such studies to gather data that can be used to refine the ABM framework and validate its predictions.

Enhanced Collaboration with Stakeholders: Finally, future work should emphasize deeper collaboration with a broader range of stakeholders, including city planners, logistics providers, and consumers. This will ensure that the models are not only technically robust but also aligned with the practical needs and expectations of those involved in urban logistics.

In this regard, future research can significantly advance the integrated modelling framework presented in this deliverable, contributing to more sustainable, efficient, and user-friendly urban logistics systems.

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Annex I: Input Data Preparation for MASS-GT for Thessaloniki LL

1. Data processing

Zones: The raw zonal data of the Thessaloniki LL looks like the following (Figure 44):

locker_zones_enriched_demand_population_income_DELFT — Features Total: 120, Filtered: 120, Selected: 0

	lat_locker	lon_locker	type	people_cou	sample_dem	income
1	40,6140368...	22,98107488...	private	221	89	22410,20911...
2	40,6395574...	22,94911801...	private	2396	22	17013,98604...
3	40,5924830...	22,9534896...	private	3505	37	26769,71656...
4	40,6453158...	22,91819971...	private	1131	116	17063,31397...
5	40,6299681...	22,96477837...	private	3327	52	22223,7638...
6	40,6405729	22,92219070	private	2718	73	17063,31397

Show All Features

FIGURE 44 THESSALONIKI LL ZONAL DATA

We have used a geographic information system called QGIS to process the data so that it could be used in our simulations. Step-by-step approach includes the following:

1. Add an AREANR column to represent the unique identifier for each zone
2. Rename the "Lat_locker" and "lon_locker" columns as latitude and longitude.
3. Save the updated shape file as Zones_Thessaloniki.

External zones, Parcel nodes and locker network: The raw parcel nodes data of the Thessaloniki LL is provided as excel file as shown in Figure 45.

	A	B	C	D
1	Name	Type	Lat	Lon
2	Company 1	Depot	40,650	22,916
3	Company 1	Depot	40,642	22,940
4	Company 1	Depot	40,552	23,018

FIGURE 45 THESSALONIKI LL DEPOT LOCATIONS

However, the MASS-GT modules require point vector shape files as an input. Hence, the following approach is followed:

2. File named "Copy_of_loc_corr" is converted into CSV format and renamed to ParcelNodes.csv, encompassing 276 nodes, including depots and lockers.

3. "ParcelNodes.csv" is added to QGIS as a point vector layer to visualize the zones and the overlapping nodes of depots and lockers.

4. An ID column is then added to "ParcelNodes.csv", using row numbers to assign unique IDs.

5. In QGIS, a join attributes by location feature is used to "combine Zones_Thessaloniki and ParcelNodes.csv", revealing that only 73 zones contain both parcel lockers (PL) and depots, while some zones lack either or both.

6. The ParcelNodes vector file is divided into three separate files: (1) depots, (2) external zones and (3) parcel locker network. Depots are used in all modules of MASS-GT. External zones are not included due to the lack of skim matrices for external zones. Parcel locker network is saved as csv text file to be used in the Parcel Market module of MASS-GT.

7. Finally, duplicates are removed, and the file is saved as "ParcelNodes.shp" which includes only depots.

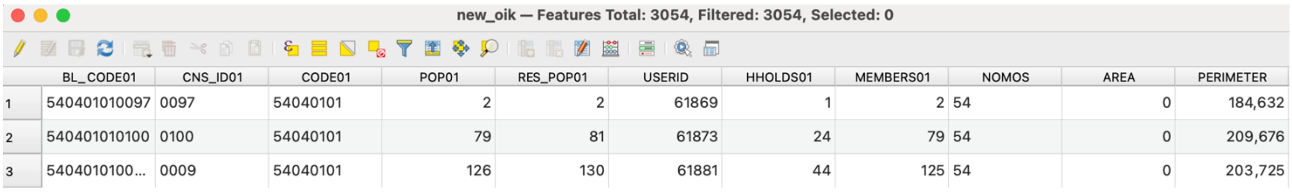
Duration and distance matrices: They are provided in a csv format which is compatible with the MASS-GT.

Courier market shares: These data are provided as an excel file and we converted this file to csv data format to be compatible with MASS-GT.

Departure times of parcels: These data were not available. After consulting with the Thessaloniki LL partners, we used a cumulative frequency distribution from MASS-GT's calibrated model for South Holland.

Sociodemographic characteristics: The stepwise approach used to process the sociodemographic data is the following:

1. The raw household data (shown in Figure 46) received from the LL is added to QGIS.



new_oik — Features Total: 3054, Filtered: 3054, Selected: 0

	BL_CODE01	CNS_ID01	CODE01	POP01	RES_POP01	USERID	HHOLDS01	MEMBERS01	NOMOS	AREA	PERIMETER
1	540401010097	0097	54040101	2	2	61869	1	2	54	0	184,632
2	540401010100	0100	54040101	79	81	61873	24	79	54	0	209,676
3	5404010100...	0009	54040101	126	130	61881	44	125	54	0	203,725

FIGURE 46 THESSALONIKI LL HOUSEHOLD DATA

2. Since the zoning of the household data and the network data are not the same, we linked these two data sources. To do this, the file "Thessaloniki_zones.shp" is uploaded into QGIS. The grey areas below show the zonal network of the Thessaloniki LL. Smaller areas represented with orange background provides information on the number of people living in these smaller zones and the number of households (see Figure 47).

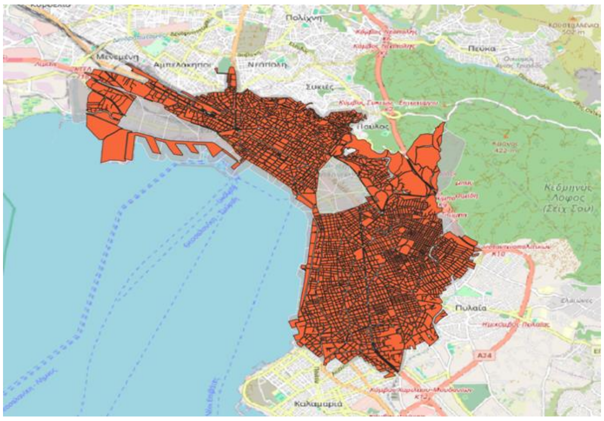


FIGURE 47 THESSALONIKI LL ZONING OF THE HOUSEHOLD DATA

3. This household data is converted into a point vector using the "QGIS tool Vector > Geometry Tools > Centroids". Figure 48 represents the point vector of the household data. This step is crucial as the data points are linked based on the geographic locations.

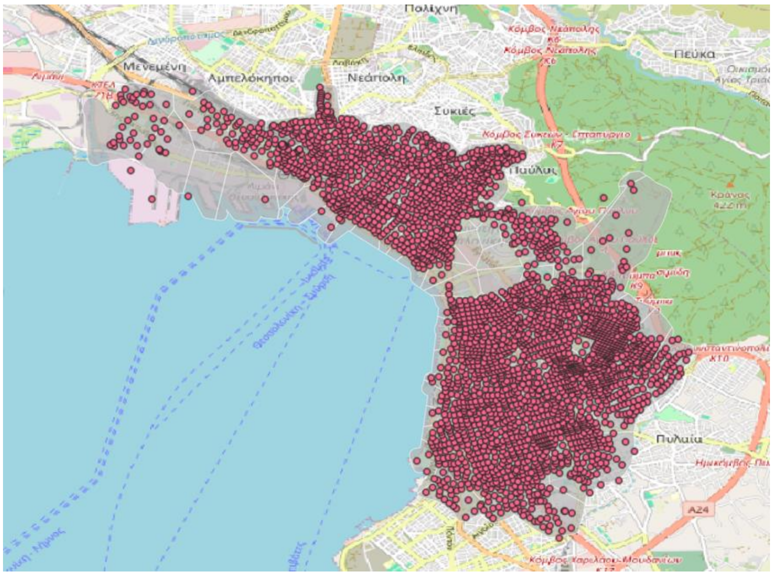


FIGURE 48 THESSALONIKI LL POINT VECTOR OF THE HOUSEHOLD DATA

4. The household data is then combined with the Thessaloniki zones using the QGIS tool "Vector > Data Management Tools > Join Attributes By Location". Figure 49 shows the AREANR which is used in MASS-GT as unique identifier and the respective number of population (POP01) and the households (HHOLDS01).

FinalHHJoined — Features Total: 3046, Filtered: 3046, Selected: 0

	AREANR	BL_CODE01	CNS_ID01	CODE01	POP01	RES_POP01	USERID	HHOLDS01
1	1	540101011409	1409	54010101	102	102	72917	44
2	1	540101012582	2582	54010101	0	0	72928	0
3	1	540101011446	1446	54010101	47	49	72952	18

FIGURE 49 THESSALONIKI LL HOUSEHOLD DATA IN QGIS

5. As can be seen from the figure above, there are multiple lines with the same AREANR. This is mainly due to the difference in granularity level of these two data sources. Hence, we created the file SEGS_2023 by summing the zonal household data for each of the zone (AREANR). The final sociodemographic data looks like the following (Figure 50):

	A	B	C	D	E	F	G
1	zone	PL_type	people_cou	sample_dem	income	POP01	HHOLDS01
2	1	private	221	89	22410,2091	3672	1339
3	2	private	2396	22	17013,986	3994	1676
4	3	private	3505	37	26769,7166	2271	859

FIGURE 50 THESSALONIKI LL SOCIODEMOGRAPHIC DATA

2. Regression analysis

The regression analysis conducted in this study aims to explore the relationship between parcel demand and two independent variables: people (population) and income (income). The overview of the script used and included in the Parcel Demand module of MASS-GT is shown in Figure 51:

```python
# ----------------- Start parcel generation -------------------------

##### Regression Analysis#####

# Characteristics DataFrame (independent variables)
characteristics = pd.DataFrame({
    'people': segs['POP01'],
    'income': zones['income'],
})

# Target DataFrame (dependent variable)
target = pd.DataFrame({'parcels': zones['sample_dem']})

# Add a constant term to the independent variables (required for statsmodels)
characteristics_with_const = sm.add_constant(characteristics)

# Create a linear regression model using the entire dataset
model = sm.OLS(target, characteristics_with_const).fit()

# Print the summary to see coefficients, p-values, etc.
print(model.summary())

# Use the model to predict parcel demand for the entire dataset
zones['parcels'] = np.round(model.predict(sm.add_constant(characteristics))).astype(int)
```

FIGURE 51 THESSALONIKI LL REGRESSION ANALYSIS (SCRIPT)

Using an Ordinary Least Squares (OLS) regression model, we found that both variables significantly predict parcel demand, with coefficients of 0.0096 for population and 0.0058 for income as shown in Figure 52.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                parcels   R-squared:                       0.189
Model:                            OLS   Adj. R-squared:                  0.175
Method:                 Least Squares   F-statistic:                     13.60
Date:                Fri, 08 Mar 2024   Prob (F-statistic):           4.90e-06
Time:                        11:14:06   Log-Likelihood:                -639.26
No. Observations:                 120   AIC:                             1285.
Df Residuals:                     117   BIC:                             1293.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -72.8453     30.063     -2.423      0.017    -132.383     -13.308
people         0.0096      0.003      3.774      0.000       0.005       0.015
income         0.0058      0.001      4.342      0.000       0.003       0.008
==============================================================================
Omnibus:                      102.471   Durbin-Watson:                   1.902
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1192.241
Skew:                           2.821   Prob(JB):                    1.28e-259
Kurtosis:                      17.374   Cond. No.                     1.36e+05
==============================================================================
```

FIGURE 52 THESSALONIKI LL REGRESSION ANALYSIS RESULTS

This indicates that increases in both population and income levels are associated with higher parcel demand. The R-squared value of 0.189 implies that approximately 18.9% of the variability in parcel demand can be explained by the model, while the adjusted R-squared value of 0.175 accounts for the number of predictors used. Despite the statistical significance of the predictors, the relatively low R-squared values indicate that other factors not included in the model may also influence parcel demand. From this analysis, we derived the income per household coefficient which is then used to predict demand for the study area.

Annex II: Input Data Preparation for MASS-GT for Helsinki LL

(1) Data processing

Zones and Parcel Nodes: The Helsinki LL provided an QGIS project including the sociodemographic characteristics (number of inhabitants and income level per zone) and the zoning of the study area.

The raw zonal data of the Helsinki LL looks like the following (Figure 53):

Zones_Helsinki — Features Total: 9, Filtered: 9, Selected: 0

	posno	toimip	nimi	nimi_ru	id	tu_kesk	ap_ask_lkm	AREANR	X	Y
1	01530	VANTAA	Veromiehenk...	Skattmansby	1	999999	999999	9	25497170,170	6689257,497
2	00100	HELSINKI	Helsinki Kesk...	Helsingfors c...	2	149165	386	1	25495799,790	6673325,642
3	00100	HELSINKI	Helsinki Kesk...	Helsingfors c...	19	85654	8290	2	25495799,790	6673325,642
4	00150	HELSINKI	Eira - Hernes...	Eira - Ärthol...	6	172687	577	3	25496064,420	6669867,998
5	00150	HELSINKI	Eira - Hernes...	Eira - Ärthol...	33	108346	745	4	25496064,420	6669867,998
6	00120	HELSINKI	Punavuori	Rödbergen	5	70392	5710	5	25496548,9...	6672247,972
7	00220	HELSINKI	Jätkäsaari	Busholmen	32	65890	6720	6	25494959,510	6670518,818
8	00180	HELSINKI	Kamppi - Ru...	Kampen - Gr...	4	80070	7564	7	25495071,940	6672283,295
9	00180	HELSINKI	Kamppi - Ru...	Kampen - Gr...	30	60800	1426	8	25495071,940	6672283,295

FIGURE 53 HELSINKI LL ZONAL DATA

The raw parcel nodes data of the Helsinki LL is shown in Figure 54.

ParcelNodes — Features Total: 1, Filtered: 1, Selected: 0

	id	AREANR	CEP	X	Y
1	1	9	DBS	25497170,170	6689257

FIGURE 54 HELSINKI LL DEPOT LOCATIONS

Duration matrix: Due to the lack of data on duration skim matrices in the LL, we have used Google OSM to calculate origin and destination pairs in seconds and restored in a .csv format.

Courier market shares: Due to the unavailability of the data on courier market shares, we have used only one company (DB Schenker) which is a project partner in the project.

Sociodemographic characteristics: As provided by the LL, we extracted data on the number of inhabitants and the income levels per zone.

(2) Regression analysis

Like the Thessaloniki LL, we have conducted a regression analysis to estimate the income coefficient which is used in the Parcel demand module of MASS-GT. To explore the relationship between parcel demand and two independent variables: people (“ap_ask_lkm”) and income (“tu_kesk”). The overview of the script used and included in the Parcel Demand module of MASS-GT is the following (Figure 55):

```
##### Regression Analysis#####

# Characteristics DataFrame (independent variables)
characteristics = pd.DataFrame({
    'people': segs['ap_ask_lkm'],
    'income': segs['tu_kesk'],
})

# Target DataFrame (dependent variable)
target = pd.DataFrame({'parcels': zones['sample_dem']})

# Add a constant term to the independent variables (required for statsmodels)
characteristics_with_const = sm.add_constant(characteristics)

# Create a linear regression model using the entire dataset
model = sm.OLS(target, characteristics_with_const).fit()

# Print the summary to see coefficients, p-values, etc.
print(model.summary())

# Use the model to predict parcel demand for the entire dataset
zones['parcels'] = np.round(model.predict(sm.add_constant(characteristics))).astype(int)

# Print the updated ParcelDemand based on the regression model
ParcelDemand = sum(zones['parcels'])
```

FIGURE 55 HELSINKI LL REGRESSION ANALYSIS (SCRIPT)

Using an Ordinary Least Squares (OLS) regression model, we found that the predictors "people" and "income" are 0.0034 and 3.008e-05, respectively. The predictor "people" is statistically significant (p-value = 0.004), implying that as the number of people increases, the number of parcels also increases. However, the predictor "income" is not statistically significant (p-value = 0.621), indicating no strong evidence that income affects the number of parcels. Since there has been no other input data found for the UC and the coefficient is a small number, we have added income coefficient into the model (Figure 56).

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                parcels   R-squared:                       0.875
Model:                            OLS   Adj. R-squared:                  0.825
Method:                 Least Squares   F-statistic:                     17.48
Date:                Fri, 15 Mar 2024   Prob (F-statistic):            0.00554
Time:                        09:39:24   Log-Likelihood:                -22.102
No. Observations:                   8   AIC:                             50.20
Df Residuals:                       5   BIC:                             50.44
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -1.9047      7.840     -0.243      0.818     -22.059      18.249
people         0.0034      0.001      4.903      0.004       0.002       0.005
income      3.008e-05   5.72e-05      0.526      0.621      -0.000       0.000
==============================================================================
Omnibus:                        0.133   Durbin-Watson:                   1.799
Prob(Omnibus):                  0.936   Jarque-Bera (JB):                0.101
Skew:                          -0.051   Prob(JB):                        0.951
Kurtosis:                       2.459   Cond. No.                     4.87e+05
==============================================================================
```

FIGURE 56 HELSINKI LL REGRESSION ANALYSIS RESULTS

Annex III: EU-SILC Data

The synthetic population used in the agent-based models are derived from training Wasserstein Generative Adversarial Networks on EU-SILC living condition data[11][12] from Finland and Greece for 2022 (Falck, to appear). Variables included are listed in Table 31 and Table 32.

TABLE 31 VARIABLES INCLUDED IN THE SYNTHETIC DATA (1-31)

#	Description EU-SILC 2022	Type	# Values	Name
1	Year of birth	numerical (int)	5	Age
2	Marital status	nominal	5	PB190
3	Buy new cloths	nominal	3	PD020
4	Two pairs of shoes	nominal	3	PD030
5	Get together friends	nominal	3	PD050
6	Leisure	nominal	3	PD060
7	Spend money personal	nominal	3	PD070
8	Internet at home	nominal	3	PD080
9	Self-perceived health	ordinal	5	PH010
10	Activity reduction	nominal	3	PH030
11	Access to healthcare	ordinal	2	PH040
12	Access to dental care	ordinal	2	PH060
13	Self-defined economic status	nominal	8	PL032
14	Life satisfaction	ordinal	11	PW010
15	Satisfied financial situation	ordinal	11	PW030
16	Being happy	ordinal	5	PW090
17	Satisfied leisure	ordinal	11	PW120
18	Satisfied personal relations	ordinal	11	PW160
19	Trust in others	ordinal	11	PW191
20	Feeling lonely	ordinal	5	PW230
21	Feeling left out	ordinal	5	PW241
22	Participate as citizen (PS102)	nominal	4	activePolitical
23	Afford holiday (HS040)	binary	2	affordHoliday
24	Do artistic activities (PS041)	ordinal	6	artisticActivities
25	Manage expenses (HS060)	binary	2	capacityExpenses
26	Go to cinema (PS010)	nominal	8	cinema
27	Contact with family (PS070)	ordinal	6	contactFamily
28	Contact with friends (PS080)	ordinal	6	contactFriends
29	Education level (PE041)	ordinal	6	education
30	Ends meet (HS120)	ordinal	6	endsMeet
31	Get help (PW180)	binary	2	getHelp

[11] EU statistics on income and living conditions - Eurostat (europa.eu), last access on 22/08/2024.
[12] GESIS: MISSY - Series: EU-SILC, last access on 22/08/2024.

TABLE 32 VARIABLES INCLUDED IN THE SYNTHETIC DATA (32-58)

#	Description EU-SILC 2022	Type	# Values	Name
32	Sum personal benefits > 0	binary	2	hasBenefits
33	Access to car (HS110)	nominal	3	hasCar
34	Access to computer (HS090)	nominal	3	hasComputer
35	Long term health problem (PH020)	binary	2	hasIllness
36	Sum personal income > 0	binary	2	hasIncome
37	Afford meals (HS050)	binary	2	hasMeals
38	High household income	numerical (percentile)	2	highHIncome
39	High income	numerical (percentile)	2	highIncome
40	Household size (PB030)	numerical (int)	5	householdSize
41	Household size (HB120)	numerical (int)	5	householdHSize
42	Household type (HB110)	nominal	7	householdType
43	Gender	binary	2	isFemale
44	Attend live performance (PS020)	nominal	7	livePerformance
45	Attend sport events (PS040)	nominal	8	liveSport
46	Low household income	numerical (percentile)	2	lowHIncome
47	Low income	numerical (percentile)	2	lowIncome
48	Medium household income (HY020)	numerical (percentile)	2	mediumHIncome
49	Medium income	numerical (percentile)	2	mediumIncome
50	Occupation (PL051)	nominal	52	occupation
51	Reading books (PS042)	nominal	8	readBooks
52	Region NUTS 1 or 2 (DB040)	nominal	x	region
53	Size of place (DB100)	ordinal	3	sizePlace
54	Tenure status (HH021)	ordinal	5	tenureStatus
55	Visit cultural sites (PS030)	nominal	7	visitCulture
56	Visit family (PS050)	ordinal	6	visitFamily
57	Visit friends (PS060)	ordinal	6	visitFriends
58	Contribute voluntarily (PS110)	nominal	6	voluntary

Preparation of Data

Cross-sectional EU-SILC data for 2022, combined with individual data records from EUROSTAT for Finland and Greece, are used to generate a full-scale synthetic population for the Helsinki and Thessaloniki municipalities. A two-step process starts with demographically balancing the training data and finalising training for the neural network model with balanced data. The balancing process is sketched out below. The neural network model uses a one-hot encoded vector for each individual and cannot handle missing values. Hence, missing values on variables over a limit of 0.67 for Finland and 0.5 for Greece result in that variable being removed. The different tolerance levels are chosen for convenience to keep the same variables in both data sets. “KNNImputer” or “IterativeImputer” (ScikitLearn) imputes the remaining variables with missing values. Next, all variables, independent of data type, are translated into categorical variables that can be transformed into so-called one-hot-encoded variables. That is to create a vector of size, the number of values on a particular variable, and give this vector zero values for all but the cell referring to the actual value. For each data record, the size of the complete vector is 294 for Finland and 295 for Greece. The difference refers to the variable Marital status (PB190) in Finland having one less category than the general EU-SILC. This vector represents the total of 57 variables listed below.

Weighting of Data

The synthetic populations are created by training a Wasserstein generative adversarial network on EU-SILC cross-sectional data from 2022 for the respective countries. Before training the model that outputs the final synthetic population, the datasets need to be balanced. For Helsinki a demographic profile of age-group, gender and education was used to expand the original data with randomly selected data records from a neural network model trained on the original data. For Thessaloniki the person weights indicating how many people in the actual population one data record represented were used to approximate a discrete number. The original data record was duplicated n-times according to this number to frame a balanced population. After balancing, the new datasets were used to train the Wasserstein generative adversarial network that finally outputs the synthetic population.

Wasserstein Generative Adversarial Network Producing Synthetic Populations

Generative adversarial networks (Goodfellow et al., 2014, Arjovsky et al., 2017) consist of two neural nets. The first is a critic checking whether a generated data record is fake or real. The second is a generator that generates "fake" data records. The two networks are set up against each other by feeding the critical data records produced by the generator. The critic receives a mix of generated or "fake" and actual examples and gradually improves its capability of distinguishing the two. Simultaneously, the generator must improve its "fakes" to fool the critic. When the model has been trained to convergence, which means that with the set network parameters, it cannot produce any better results, the generator becomes good at producing convincingly "real" data records. By inputting a batch of random vectors, the trained generator produces a corresponding number of data records highly like the data used to train the model. The training data are either plain originals, reweighted by replacement or originals imputed by the results from a model trained only on originals. The Wasserstein generative adversarial network (Arjovsky et al., 2017) uses the Wasserstein distance to measure loss. Penalty function turnouts accompany this measure to prevent the adversarial model from collapsing into only reproducing the most dominant data examples. The synthetic populations in this project are produced according to these principles and are like the implementation used in (Garrido, 2020).

Annex IV: Consumer Demand Thessaloniki

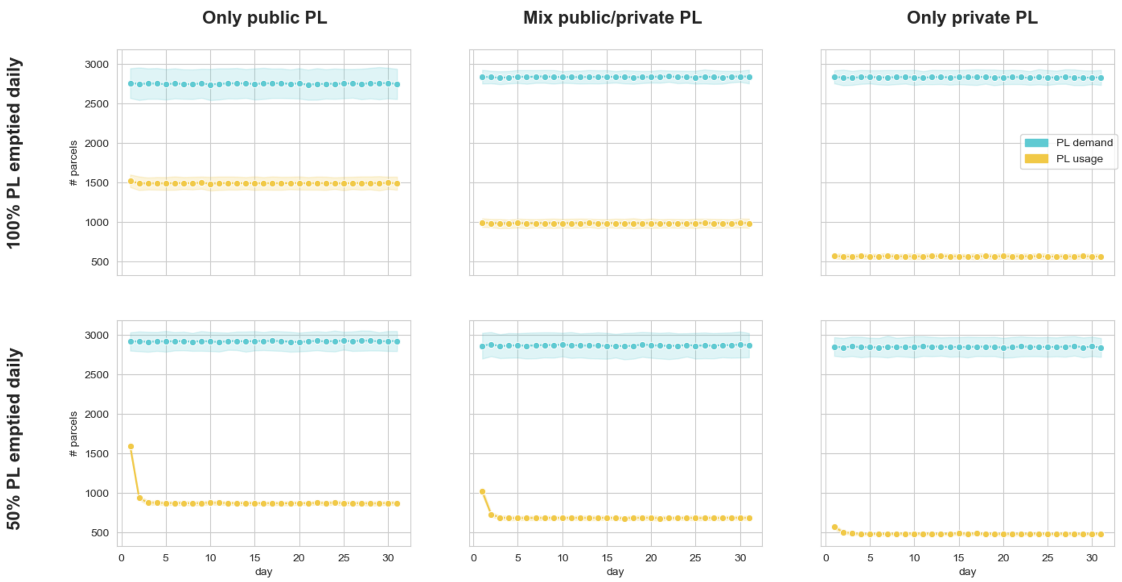


FIGURE 57 PARCEL LOCKER DEMAND AND USAGE OF CONSUMERS WITH A SLIGHT PREFERENCE FOR PARCEL LOCKERS (5B) AND PARCEL LOCKERS WITH A CAPACITY OF 34 PARCELS (2A). RELEVANT SCENARIOS: 15, 13, 17, 16, 14, 18.

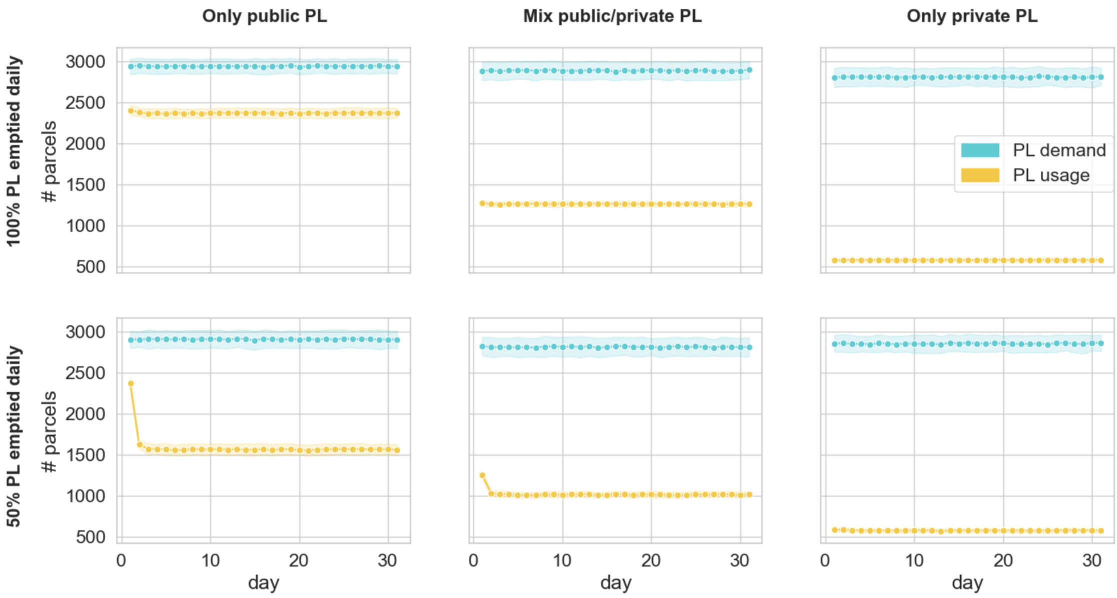


FIGURE 58 PARCEL LOCKER DEMAND AND USAGE OF CONSUMERS WITH A SLIGHT PREFERENCE FOR PARCEL LOCKERS (5B) AND PARCEL LOCKERS WITH A CAPACITY OF 68 PARCELS (2B). RELEVANT SCENARIOS: 21, 19, 23, 22, 20, 24.

Annex V: Delivery Schedules Thessaloniki

Delivery schedules for consumers with a slight preference for PLs are provided below for capacities of 34 parcels and 68 parcels, respectively. The pattern of the delivery tour, including PL type, PL utilization, and capacity, does not show any significant differences for consumers who prefer PL delivery. The only main difference observed is the volume increase, as shown in Figures 35 and 36 below.

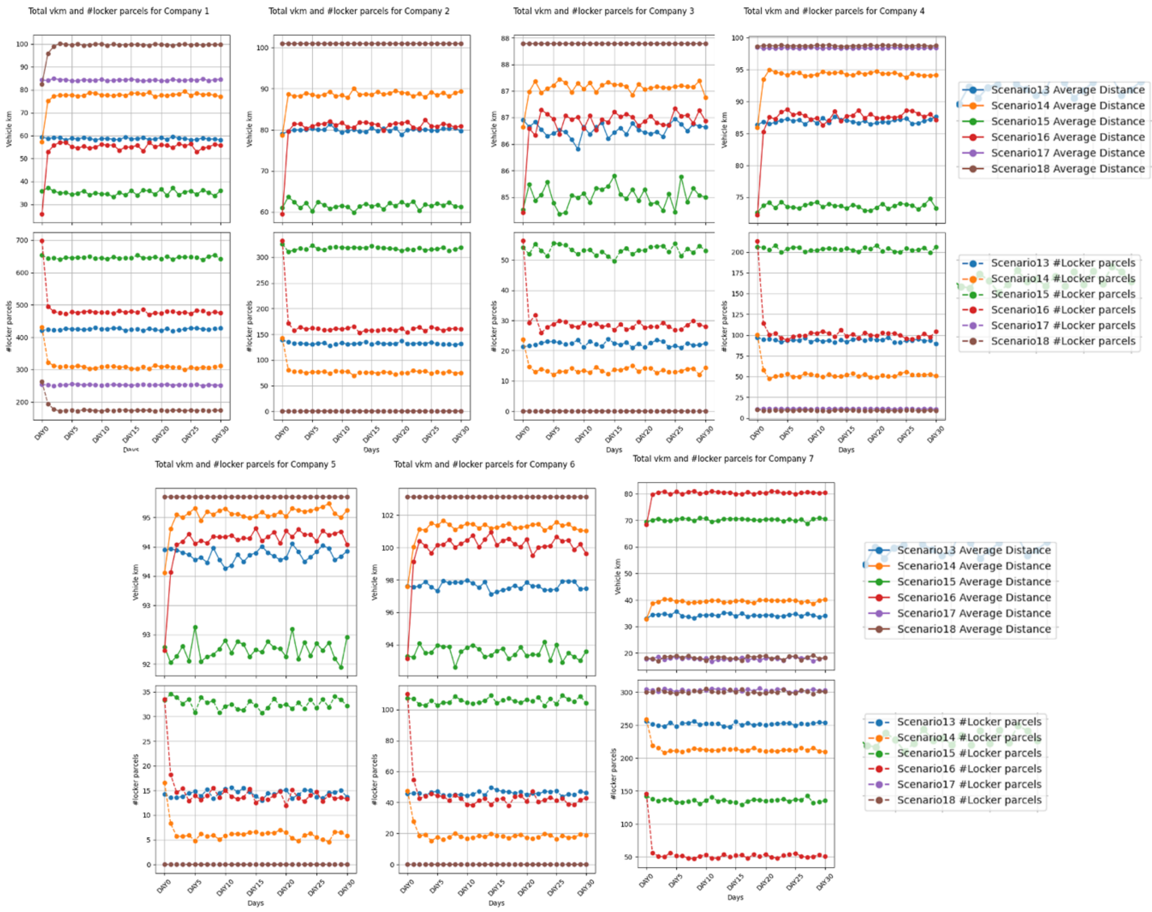


FIGURE 59 DELIVERY SCHEDULES FOR PL TYPE AND UTILISATION FOR CAPACITY OF 34 (SCENARIOS 13-18)

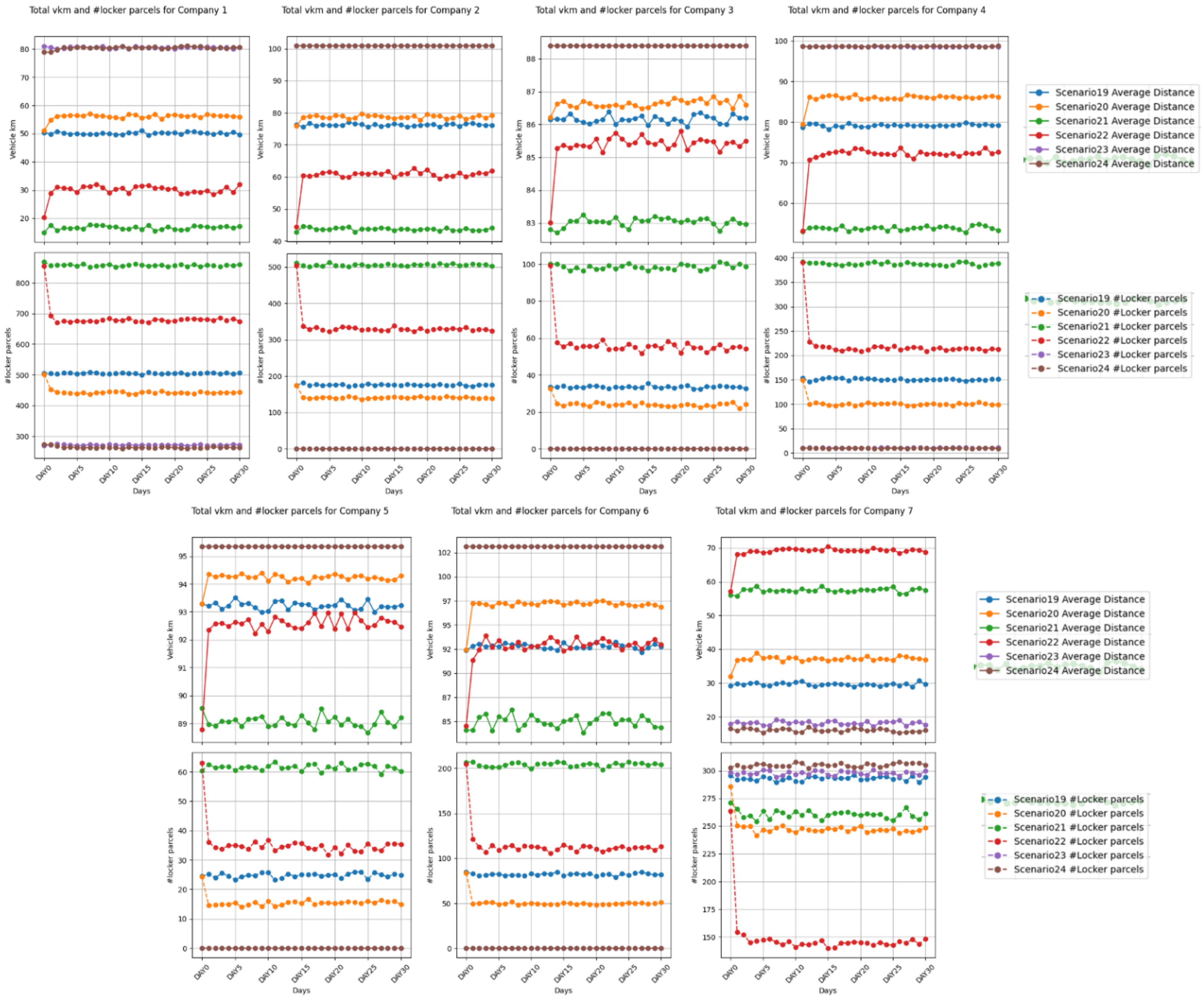


FIGURE 60 DELIVERY SCHEDULES FOR PL TYPE AND UTILISATION FOR CAPACITY OF 68 (SCENARIOS 19-24)