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ORIGINAL RESEARCH

A simulation-driven approach to last-mile logistics analysis considering microlevel operational sequences for efficient delivery planning

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Abstract
Supply chain management is becoming more challenging due to shifting client expectations and ongoing technological advancements. Failure to implement these changes can lead to resource mismanagement, delivery delays, and high operational costs. To address these challenges, this study presents a hybrid simulation framework combining Discrete Event Simulation (DES) and Agent-Based Modeling (ABM) for efficient decision-making. The proposed framework uses micro-level task modeling with the Maynard Operation Sequence Technique (MOST) to estimate delivery service times. In addition, Monte Carlo simulation examines output variability, and the Wasserstein distance-based double bootstrap method provides statistical validation. This holistic approach enables informed, data-driven decisions to avoid resource underutilization, ensure proper staff allocation, and maintain service consistency. Simulation scenarios revealed that incorrect planning can lead to unmet delivery commitments or excessive staffing costs. Experimental results indicate that the micro-level framework outperformed the existing simulation (Macro/Traditional) in operational efficiency. The proposed framework is benchmarked against exact MILP-VRP (Mixed Integer Linear Programming) optimization and heuristic ALNS (Adaptive Large Neighborhood Search) approaches. Compared to existing approaches, the proposed approach achieved higher efficiency by increasing deliveries by 28% with fewer fleets, increasing vehicle utilization to 98%, reducing elapsed time, and reducing delivery penalties. This approach was thoroughly validated using GIS-based data, experimentation, and performance analysis, showcasing its effectiveness in optimizing operational efficiency and profitability.

Keywords Route planning · Anylogicsimulation · Last mile delivery (LMD) · Micro-level analysis · Wasserstein distance · GIS · Vehicle routing problem (VRP)

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1 Introduction

The rapid rise of e-commerce and on-demand delivery services has underscored the need for efficient LMD planning and implementation. Advanced decision support technologies are crucial for optimizing operations and addressing urban logistics difficulties, including traffic congestion, shifting consumer needs, and route optimization. Conventional logistics models often cannot capture the intricacies of micro-level delivery task sequencing (from dispatch to doorstep), leading to inefficient route planning and higher operational costs. Last-mile logistics in business-to-consumer (B2C) is widely recognized as one of the most expensive, least efficient, and most environmentally challenging stages of the supply chain (Gevaers et al., 2014). A major reason is the use of traditional logistics models that rely on macro-level routing decisions (aggregates/sums) and do not account for micro-level delivery activities (steps/details) from dispatch to doorstep, such as parking, customer confirmation, building access, package handling, etc. This operational gap can reduce routing efficiency and increase delivery costs. For instance, Punakivi et al. (2001) conducted a simulation study using real-world data (in Finland) where the delivery costs typically range between €2 and €6 per parcel, heavily influenced by customer density and urban congestion. Major cost drivers include traffic delays, parking limitations, and unsuccessful delivery attempts due to customer absence (Punakivi et al., 2001). Furthermore, Song et al. (2018) report high first-time delivery failure rates worldwide, ranging from 12 to 60% (Song et al., 2018). These inefficiencies increase labor costs and jeopardize service reliability. Similarly, recent studies published in 2026 report that global retail e-commerce sales have expanded more than fourfold over the past decade, rising from approximately $1.34 trillion in 2014 to $6.00 trillion in 2024 (Statista, 2025), according to Statista. Despite this rapid growth, LMD remains one of the most complex and expensive components of urban logistics, accounting for nearly 53% of total distribution costs (Zadeh et al., 2026). To tackle these challenges, our study proposes a unified computer simulation framework that combines ABM and DES to optimize delivery operations through dynamic task assignment and shortest-path optimization. In this framework, ABM captures interactions among individual delivery agents by simulating their decisions and movements, while DES models logistical processes, such as vehicle dispatching and package handling, at the operational level to improve delivery efficiency. Micro-level delivery also involves numerous interdependent factors, such as order fulfillment, delivery operator mobility rate, vehicle dispatch speed, and location-specific constraints (elevator availability, parking limitations). Unlike existing optimization methods, this approach can incorporate the dynamic uncertainties of urban delivery settings and enable more robust and adaptive decision-making. To consider all these factors, our approach leverages AnyLogic's multi-method modeling capabilities to provide a comprehensive way to analyze and improve delivery efficiency. It also focuses on developing an integrated model that dynamically optimizes task sequencing, route planning (based on geospatial longitude & latitude), and system-wide performance evaluation. The main objective of this study is to design a multi-operational system that integrates the ABM for capturing individual delivery agents' behavior (high-level abstraction), and DES for simulating logistics processes for the end delivery (order processing, dispatching). Hence, it aims to improve LMD delivery efficiency, resource utilization, and delivery reliability by dynamically analyzing supply chain behavior and optimizing delivery routes (shortest path & task sequencing) to reduce both costs and delivery time (Fig. 1).

It involves the modeling of delivery agents' behavior using εStatechartsε to represent the driver's decision-making with real-time route adaptation, and simulating logistics

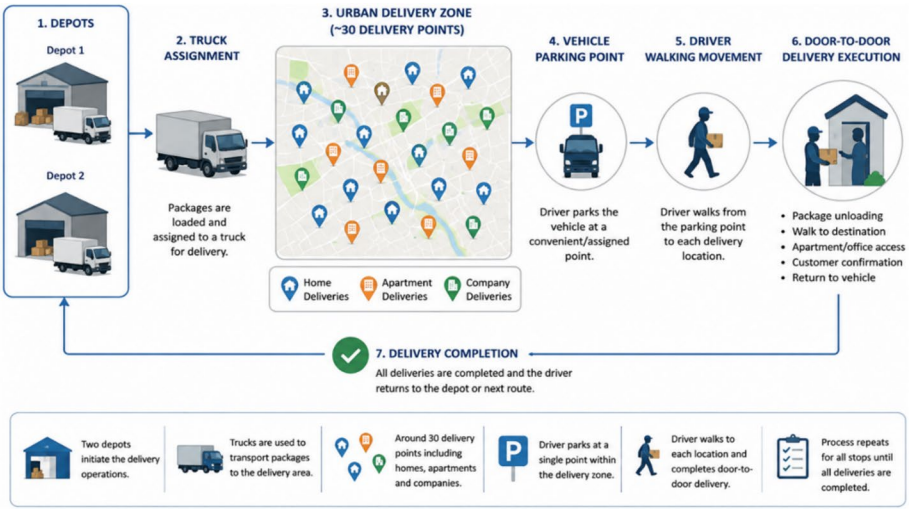

Fig. 1 Schematic View of Last-mile Logistics Operations

operations through DES for package handling and fleet management. Since modern supply chains are highly interconnected, effective route planning must account for carrier responses to routing strategies. Decision-making in route guidance directly influences delivery operators' route-selection behavior, thereby affecting overall logistics efficiency. A survey conducted nearly a decade ago on the application of simulation in manufacturing and business revealed that DES, SD, and ABM were the most utilized approaches in operational research for modeling business problems (Zolfpour-Arokhlo et al., 2013). Researchers are actively developing alternative delivery strategies and technological solutions to address the delivery inefficiencies. Innovations such as unattended delivery systems, automated lockers, and intelligent route optimization are being explored to minimize delivery failures, reduce labor costs, and improve overall last-mile efficiency. For instance, Badiee et al. (2024) integrate optimization techniques and ABM to enhance their cold supply chain (Badiee et al., 2024). They explain that a case study in Rwanda demonstrates the model's effectiveness in reducing product loss and optimizing cold chain infrastructure using AnyLogic simulations. Another study by Ikai et al. (2021) also explains that route planning is essential for managing varying demands, adapting routes to demand shifts, and integrating data from GIS to improve real-world applicability (Ikai et al., 2021). Based on the above discussion, strategic route planning, when integrated with a hybrid agent, is highly important in the domain of SCM (Supply Chain Management). Therefore, to improve carrier deliveries within the supply chain, our study aims to provide better data analysis using simulation tools such as AnyLogic and ergonomic tools such as MOST for data collection. Additionally, we integrated Monte Carlo Analysis for time-variation analysis and data-oriented carriers to provide a tool to optimize deliveries within the El Paso area. Notably, this study emphasizes the significance of micro-level data analysis in achieving optimal results for carrier companies. It also shows that inaccurate analysis can lead to incorrect delivery commitments, resulting in customer loss. Hence, implementing effective route planning can minimize unnecessary movement and improve resource utilization. It is critical to optimizing overall supply chain performance and is a central focus of our analysis. While supply chain discussions often emphasize global networks, micro-level analysis can

yield meaningful insights that drive performance improvements, particularly in areas like localized carrier distribution. To advance routing and planning within SCM, much existing research has focused on improving transportation operations through mathematical optimization models. Our focus reflects the growing recognition that effective logistics planning (micro-operational and optimization-driven approaches) is essential for achieving agility, responsiveness, and cost efficiency in modern supply chains. However, few studies have integrated detailed micro-level task analysis with simulation-based routing frameworks with proper benchmarking. This framework supports data-driven operational decision-making and provides a platform for evaluating routing strategies under realistic operating conditions. By incorporating execution-level delivery activities and service-time variability, it captures important operational characteristics that are often simplified in conventional routing models. It includes parking delays, walking distances, elevator usage, security procedures, and heterogeneous delivery behaviors. Accordingly, our proposed study makes the following key contributions:

This study proposes a GIS-integrated agent-based optimization framework that jointly models task partitioning, depot selection, and shortest-path routing under micro-level delivery considerations.
The research estimates the delivery service time by modeling it with a MOST-based simulation model that includes ergonomic parameters.
The study examines the effects of different types of deliveries by examining the distribution patterns of different types of delivery (residential, apartment, and commercial) with the help of GIS-based spatial analysis.
Benchmarks the proposed framework with the MILP-VRP optimization and heuristic ALNS approaches to test the proposed routing performance and computational trade-offs.
The framework provides a robust method for determining the optimal fleet size to meet delivery demand efficiently.

The subsequent sections of this study are organized as follows. Section 2 provides a brief description of relevant literature in this field. Section 3 presents a step-by-step methodology by analyzing the simulation framework, and Sect. 4 validates the framework statistically and with a real-world dataset. Section 5 summarizes the results and discussions of this study. Finally, Sect. 6 summarizes this article with some potential future extensions and practical implications (Sect. 7).

2 Related Works

With e-commerce expanding at an unprecedented rate and expectations for faster deliveries rising, the complexity of urban logistics has underscored the need for more efficient and innovative LMD solutions. As a result, in recent years, simulation-based methods have become more common to model, analyze, and optimize these challenges. As reported by Steven et al. (2003), selecting optimal routes from multiple pick-up and delivery points and understanding how this affects later operations is one of the main challenges in last-mile logistics (Steven et al., 2003). Technological advances have also revolutionized the logistics sector by enabling real-time information sharing across the network, creating integrated and responsive supply chain systems. As Hu and Haddud (2020) note, these

developments have accelerated the adoption of artificial intelligence (AI), simulation models, and data-driven tools to improve decision-making, operational accuracy, and customer satisfaction (Hu & Haddud, 2020). These new technologies are crucial in today's supply chain and logistics environment for achieving optimal outcomes. Accordingly, Adetiloye and Perez (2015) emphasized strategic decision-making that considers socio-cultural factors, economic conditions, and environmental constraints, as well as stakeholder collaboration. On the micro level, these decision-making criteria play an important role in improving city logistics operators' activities. Yet the approach remains largely theoretical, and no simulation-enabled framework translates strategies into data-driven models that can guide action (Adetiloye & Pervez, 2015). In this context, Barcos et al. (2010) showed that route optimization is a key element in addressing complex logistics problems. Especially for less-than-truckload carriers that need to consolidate smaller loads efficiently to limit operating costs while meeting service-level requirements (Barcos et al., 2010). Another recent study by Cook and Lodree (2025) models vehicle dispatch from multiple production areas to a single distribution point, focusing on policy-level optimization under stochastic demand (Cook & Lodree, 2025). Depending on volume and demand patterns, these carriers must identify optimal routing strategies, whether through direct delivery, break-bulk terminals, or collection/peddling systems. Meanwhile, the COVID-19 pandemic exposed critical vulnerabilities in global supply chains. In a study, Ozdemir et al. (2022) showed how poor planning and rigid systems led to widespread disruptions, increased costs, and sector-wide failures (Ozdemir et al., 2022). These developments highlighted the growing need for resilient and adaptable logistics strategies. Conventional planning tools were often inadequate in handling extended and complex disruptions. Consequently, organizations increasingly adopted flexible, technology-driven approaches. Among these, simulation technologies have emerged as valuable tools for evaluating alternative strategies, enhancing decision-making, and modeling dynamic operational scenarios in near real time. For instance, Zee & Vorst, (2005) showed that simulation-based supply chain systems enable practical scenario analysis, performance forecasting, and greater responsiveness, ultimately leading to more reliable and precise logistics planning (Zee & Vorst, 2005).

To solve complex supply chain issues and optimize outcomes, many companies have turned to simulation software and mathematical analysis. By integrating simulation techniques into logistics, businesses can evaluate various delivery scenarios and their potential outcomes without the risks of real-world testing. However, the accuracy of these simulations largely depends on data reliability. Therefore, it's important to study scenarios and identify the data and information needed for a successful simulation. For instance, Wagner and Frankel (2000) found that carriers that employ advanced technologies are better able to compete in changing markets. They also highlighted the importance of strong customer relationships and flexible service offerings to maintain competitive advantage. By doing so, they not only improve their own operational performance but also contribute to greater efficiency and competitiveness across the entire supply chain. They optimize service delivery, align with shippers' goals, and leverage technology; carriers are positioning themselves as vital links in the supply chain (Wagner & Frankel, 2000). Another study shows that logistics operations in SCM are among the most important fields affecting strategic decisions. They suggested a hybrid simulation–optimization method that uses overall effective equipment analysis and loading schedules in the production environment to optimize transportation time and cost (Khezeli et al., 2021). In recent years, researchers have simplified complex design systems for the optimal routing problem in SCM design. Specifically, Vaka (2024) proposes a data-centric approach to enhance inefficiency in LMD for SCM through AI optimization. It is also limited to considering the door-to-door delivery

system, using a small task segmentation (Vaka, 2024). Givindan et al. (2014) propose a two-echelon multiple-vehicle location routing model for sustainable SCN (Supply Chain Network) design and optimization of economic and environmental objectives for a perishable food SCN (Govindan et al., 2014). Another study underscores the importance of micro analysis in LMD services for assessing the impact of adjustments in operational efficiency and service diversification in the motor carrier industry (Peinkofer et al., 2020). This way, companies can better meet customer demand, address service-time issues, and minimize delays. Moreover, Sahay & Ierapetritou (2013) propose optimal resource allocation decision-making strategies and agent-based simulation that mimics the complex and dynamic nature of the supply chain (Sahay & Ierapetritou, 2013). Other researchers seek optimal solutions using GIS systems, alongside many studies in AI-based planning and mathematical applications. It also helps visualize intricate logistics networks and make informed decisions in real time using spatial information and algorithmic optimization. Qu (2024) argues that integrating GIS is indispensable in modern logistics to make the supply chain more cost-efficient (about a 12% delivery efficiency improvement) and resilient (Qu, 2024). Strategic use of GIS and route optimization technology supports successful SCM in modern logistics (Helo & Rouzafzoon, 2023). However, several studies have noted that many users lack a clear understanding of the underlying algorithms and modeling assumptions, leading to suboptimal or misleading outcomes. Furthermore, many GIS systems use heuristic methods, which do not offer a level of transparency regarding the quality of the result and guarantees of good performance, thus casting doubt on the reliability of the GIS, especially for logistics applications where the success of the system is crucial. However, Murray (2021), Tong & Murray (2012), and Ligmann-Zielinska (2016) argue that increasing dependence on GIS in business analytics highlights GIS's potential to transform traditional decision-making processes (Ligmann-Zielinska, 2016; Murray, 2021; Tong & Murray, 2012). Hence, integrating GIS with optimization techniques is a common practice to increase the effectiveness and precision of SCM. It plays a vital role in route optimization and streamlining logistics operations by enabling the processing and analysis of spatial data. This technology provides companies with strong solutions for complex supply chain challenges. Recently, there has also been a growing need to integrate digital twins, optimization, and intelligent decision-making into modern supply chain operations. For instance, Shadkam and Irannezhad (2025) explain that the modern supply chain is shifting from traditional simulation models to an agent-based intelligent digital supply chain, where optimization and adaptive decision logic can enhance operational effectiveness and responsiveness in the presence of uncertainties. They also review the increasing development of simulation optimization methods and the possibility of combining exact and heuristic optimization approaches in complex logistics systems (Shadkam & Irannezhad, 2025). Previously, Shadkam and Bijari (2017) applied multi-objective simulation optimization and mathematical programming for supplier selection and order allocation with uncertainty. Their findings showed that optimization can effectively support simulation-based decision-making environments. (Shadkam & Bijari, 2017). Likewise, Barat et al. (2022) developed an agent-based digital twin of a parcel sorting operation to improve logistics efficiency and resilience (Barat et al., 2022), and Thogaru et al. (2025) extended the use of digital twins to improve logistics operations (Thogaru et al., 2025). Our research builds on these trends by combining hybrid simulation with MILP-VRP and ALNS benchmarking to optimize last-mile logistics operations. With strategic application, the advantages of these capabilities can result in significant cost savings, increased quality of service, and greater sustainability, all contributing to more resilient and adaptive supply chain networks. Previous studies have contributed to improving LMD operations. Yet, many studies still focus

on isolated techniques without fully integrating key elements such as spatial data, agent-based behavior, and process-based simulation. Therefore, to develop an accurate representation of delivery activities, this study employs the MOST for data collection. Maynard introduced MOST in 1960, and it has been widely used since 1967. It provides a structured work-measurement system that measures operational tasks at a micro level using predefined motion sequences and time standards.

MOST differs from previous approaches, such as Methods-Time Measurement (MTM), which focused on individual motions, by concentrating on standardized sequences of actions. It streamlines complicated tasks with three basic sequence models: General Move, Controlled Move, and Tool Use. Each addresses specific action types, such as free movement, controlled motion, and tool-related activities. MOST supports accurate task-time calculations, as discussed by Tuan et al. (2014), Golabchi et al. (2015), and Marasabessy et al. (2023), enabling organizations to establish consistent, repeatable operational efficiency (Golabchi et al., 2015; Marasabessy et al., 2023; Tuan et al., 2014). Furthermore, stopwatch time study is a crucial part of MOST and has become increasingly important in competitive industrial production. It affects productivity, reduces wasted time, and helps to achieve targets. To enhance the reliability of the collected data, Monte Carlo simulation techniques were integrated into the analysis. This approach is well known as an effective technique for assessing demand fluctuations, lead times, and inventory levels, especially in multi-echelon, complex supply chains. Several researchers have suggested it for statistical validation. For instance, Belvardi et al. (2012) highlight that Monte Carlo Analysis not only provides a range of possible outcomes but also supports effective risk assessment and decision-making. When paired with sensitivity analysis, it further strengthens the understanding of how input variables influence critical performance indicators such as service levels and inventory costs (Belvárdi et al., 2012).

Although simulation and optimization methods are increasingly adopted in LMD research, a significant gap (Table 1) remains in capturing the full operational complexity of real-world urban logistics, particularly at the micro-motion level. While Monte Carlo simulation has proven valuable for supporting decision-making under uncertainty, most existing studies either focus on routing optimization or system-level analysis without explicitly modeling detailed delivery activities and their associated variability. To address this gap, this study proposes a unified hybrid framework that integrates micro-level task modeling with GIS-enabled simulation to better represent real-world delivery operations.

3 Methodology

This section introduces a systematic analysis of the LMD task to improve overall supply chain efficiency. The proposed framework integrates the hybrid simulation approach with region-specific GIS information and MOST analysis. As shown in Fig. 2, the framework consists of four major steps: 1) Modeling the SC behavior using an agent-based model, 2) Discrete Event Simulation (DES) for Micro-Level Analysis, 3) Performing the MOST analysis for the delivery categories, and 4) Development of a hybrid model in AnyLogic. The details of each step are described below:

Table 1 Taxonomy of existing logistics modeling approaches and comparison with the proposed hybrid framework

References	Simulation Method/ Tools	Hybrid Simulation	GIS Integration	Micro-level Task Sequencing	Validation / Benchmark	Dynamic Re-routing & Task Sequencing
Our Study	ABM, DES, Monte Carlo & MILP-ALNS Benchmarking	Yes	Yes	Yes	Yes (Real World)	Yes (MOST, Vehicle no.)
Calabrò et al., (2023)	ABM	No	Yes	No	No	No
Süß et al., (2025)	Review (DES/ABM)	No	Partial	No	No	No
Gnoni et al., (2025)	Simulation tool (DES)	No	No	No	Partial	No
Yun et al., (2025)	Heuristic routing model	No	Yes	No	Partial (model testing only)	No
Bienzeisler, (2025)	ABM	No	Partial	No	No	No
Snoeck & Winkenbach,(2022)	DES-based optimization	No	Yes	No	Partial (model validation)	No
Tiwari & Sharma, (2023)	MILP routing	No	No	No	No	No
Ramírez-Villamil et al.,(2023)	ML + Routing	No	Yes	No	Yes	No
Krendeleva et al., (2025)	Simulation	No	Yes	No	No	Partial (mixed robot-truck setup)
Liu & Wang, (2025)	Routing + traffic simulation	No	Yes	No	Partial	No
Shadkam, (2022)	Cuckoo Optimization + Network Design	No	No	No	Metaheuristic	Partial
Barat et al., (2022)	Agent-Based Digital Twin for Parcel Sorting	No	No	Yes	Simulation based	Focus on sorting, not delivery routing
Rajabi et al., (2024)	Multi-objective network optimization	No	No	No	GA Benchmark	Abstract pandemic-level modeling
Thogaru et al., (2025)	Digital Twin for Sorting Terminals	Yes	No	Yes	simulation Based	Terminals Optimization

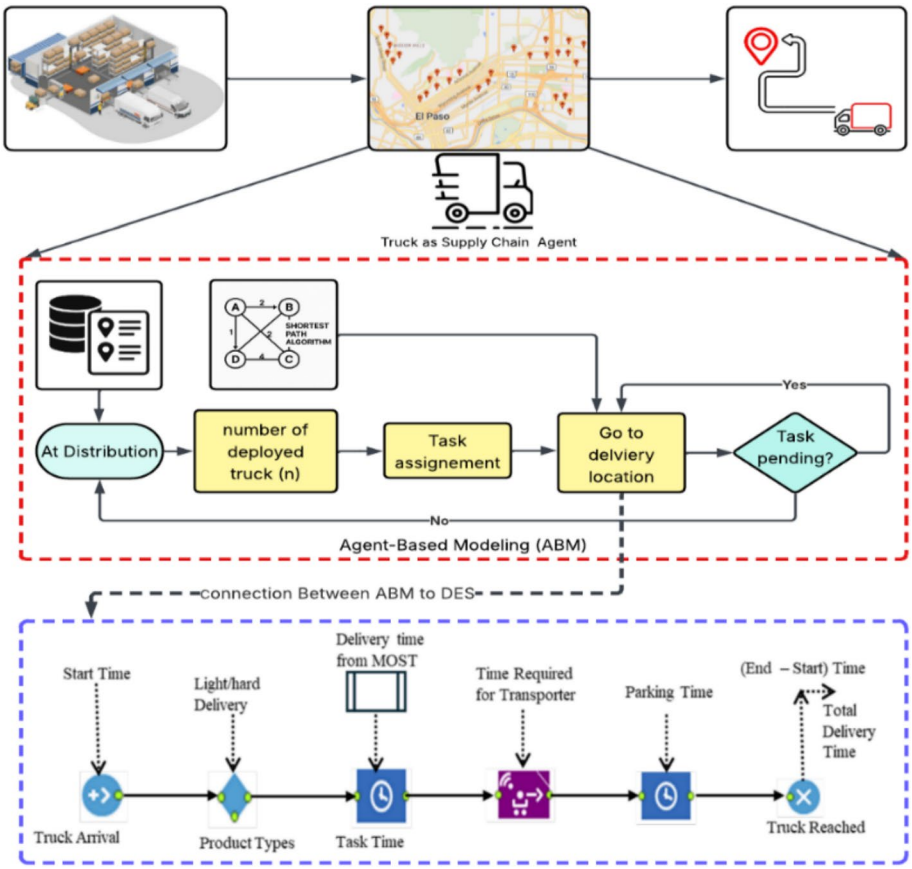

Fig. 2 Framework of the Proposed Hybrid Simulation Model

3.1 Modeling the SC behavior using an agent-based model

This section introduces the agent-based modeling used to simulate the step-by-step delivery process from the distribution center (DC) to end users. The model captures operational behavior to meet daily delivery targets. The typical delivery process includes not only receiving instructions from the DCs, but also determining the delivery route, reaching the customer address, locating the delivery point, making the delivery, and then proceeding to the next addresses. In this case, the delivery truck (accompanied by one deliveryman) is considered as the agent (*Truck*) to perform the delivery tasks. This model involves some important decision factors, including the number of agents (n) to be deployed, assigning delivery tasks to individual agent, the targeted delivery locations ($Latitude_i$, $Longitude_i$) for each agent, and the optimal route ($Route_{Truck}$) for completing delivery. The specific simulation components and Process Modeling Library elements employed in developing DES for the last-mile logistics framework are summarized in Table 2.

The number of agents (n) is a key decision variable for the DCs, carefully determined to maximize the gain while fulfilling the delivery requirement. It also determines the number of assigned tasks and the selection of the delivery route. As discussed at the beginning

Table 2 AnyLogic SYMBOL & NAME WITh specified role in the research for ABM & DES

Symbol	Component name	Role in this research
	Source	Dynamically generates customer delivery requests/orders in the simulation model
	Queue	Stores pending delivery tasks before truck assignment when vehicles are unavailable
	Delay	Represents service delays (parcel loading, unloading, and MOST-based service execution time)
	Branch	Evaluates routing decisions (truck delivery, move to next customer, or return to depot)
	Sink	Removes completed delivery orders after fulfillment
	Truck (Agent)	Represents delivery vehicles performing transportation and package delivery operations
	Customer Agent	Represents House, Apartment, and Company delivery destinations
	GIS Node	Represents delivery coordinates using latitude and longitude data (Customer Location)
	GIS Map	Visualizes road networks, depots, and truck movement using real-world geographic routing
	Distribution Center	Starting and ending location where trucks collect parcels and return after deliveries
	Statechart	A location of control with a particular set of reactions to conditions and/or events
	Transition	Controls movement between operational states such as pickup, routing, delivery, and returning
	Pickup/Loading	Models parcel collection and loading operations before route execution
	`findAddress`	Identifies the next feasible delivery location using shortest path/GIS routing logic
	Message Event	Sends delivery completion updates from truck agents back to the distribution center
	returnToDepot	Returns truck agents to the Home Depot after completing all feasible deliveries
	`ResourcePool`	Represents available fleet resources and active truck availability

of the methodology section, the ABM is designed to manage day-to-day delivery operations. Because daily demand and target delivery addresses vary over time, the model adapts dynamically to reflect realistic operational conditions. Hence, the decision variables may not be the same every day. To support daily operations, we developed a dynamic task-assigning algorithm for daily SC operations to integrate into the ABM. This algorithm uses a database of target addresses, sorted by the shortest-path algorithm (`shortestDist-Collection`) and the number of deployed vehicles. The address database is sorted by address latitude and longitude. The output of this algorithm is a task list (targeted of delivery addresses) assigned to an individual vehicle. The primary objective of the dynamic task assignment algorithm is to facilitate flexible delivery operations, regardless of variations in the number of deployed vehicles. This dynamic assignment assumes that it will enhance operational efficiency and minimize overall delivery time. This algorithm is implemented within the simulation framework, which first checks the number of vehicles (n) selected and accordingly divides the `shortestDistCollection` into n whole subsets, with the last vehicle automatically assigned any remaining deliveries.

Algorithm 1 Dynamic micro level task assignment framework

Input:
$C \leftarrow \{1, 2, \ldots, N\}$: Set of customer locations
$D \leftarrow \{d1, d2\}$: Set of depots
$V \leftarrow \{1, 2, \ldots, n\}$: Set of vehicles
shortestDistCollection: List of delivery tasks sorted by distance
Cap_i: Capacity of vehicle i
H: Total Shift Duration
Dem_j: Demand of task j
e_j: Earliest service time for task j
l_j: Latest allowable service time for task j
$TW_j \leftarrow [e_j, l_j]$: Time window of task j
$TT_{ij} \leftarrow$ Stochastic travel time
Output:
C_d: Completed deliveries
M_d: Missed deliveries
$T_{elapsed}$: Total elapsed time
U: Vehicle utilization
Initialization:
Sort Customers based on shortest GPS distance
$T \leftarrow$ total number of tasks
$d = [\frac{T}{n}] \rightarrow$ approximate number of tasks per vehicle
for $i = 1$ *to* n:
  $S_i = \emptyset$ // Initialize task list
  $Cap_i^{rem} = Cap_i$ // Remaining capacity
  $t_i = 0$ // Current time
  $count_i = 0$ // task Counter
End for
Dynamic Assignment Procedure
for each task j in shortestDistCollection
  for each customer $j \in C$ do
    for each vehicle $i \in V$ do
      $\tilde{T}_{ij} \sim TT_{ij}$ // Sample stochastic travel time
      $arrival = t_i + TT_{ij}$ // Compute arrival time
      If: $D_{emj} \leq Cap_{rem_i}$ and arrival $\leq l_j$ **then**
        start = max (arrival, e_j) // Compute service start time
        $finish = start + S_j$ // Compute completion time
        If: $finish \leq H$ **then**
          If: $count_i < d$ OR no feasible vehicle exists **then**
          Assign customer ***j*** to vehicle ***i***
          $Route_i = Route_i \cup \{j\}$
          $Cap_i^{rem} \leftarrow Cap_i^{rem} - Dem_j$
          $t_i \leftarrow finish$
          $count_i \leftarrow count_i + 1$ // Update assigned task counter
          break
        End if
      End if
    End for
  End for
End for
  If *customer **j** is not assigned,* **then**
    Mark customer ***j*** as missed delivery
  End if
Return:
  Final route for each vehicle
  Total missed deliveries

For instance, in a delivery scenario involving three (3) vehicles and a total of 10 delivery locations, the *shortestDistCollection* list contains 10 locations $[L_1, L_2, L_3, \ldots\ldots\ldots\ldots\ldots\ldots\ldots, L_{10}]$. This list is divided into three subsets according to Algorithm 1, meaning the vehicles 1, 2, and 3 will be assigned for $[L_1, L_2, L_3]$, $[L_4, L_5, L_6]$, and $[L_7, L_8, L_9, L_{10}]$, respectively. If one vehicle is deployed, all tasks are assigned to that single vehicle. Then the algorithm dynamically evaluates each customer request across all available vehicles based on operational feasibility. For every customer task, the algorithm checks the remaining vehicle capacity $\left(Cap_i^{rem}\right)$, stochastic travel time $\left(\widetilde{TT}_{ij}\right)$, arrival time feasibility within the service window $\left([e_j, l_j]\right)$, and total shift duration constraints (H). Customers are assigned to vehicles that satisfy operational constraints while maximizing completed deliveries and reducing delivery delays. The algorithm attempts the next available vehicle if none meet the required constraints. Deliveries that are not feasible within the operational constraints are considered as "MissedDeliveries" When only one vehicle is deployed, all tasks are sequentially evaluated for that vehicle under the same dynamic feasibility rules. This updated assignment mechanism more realistically represents logistics operations by combining spatial proximity with real-time operational constraints, rather than relying on static task partitioning. The schematic diagram of ABM to analyze the supply chain behavior is shown in Fig. 3.

3.2 DES for micro-level analysis

While the ABM simulates supply chain behavior at a high level of abstraction, it overlooks many details, especially at the delivery end. Neglecting these details can lead to over- or underestimation of delivery time. Hence, this section introduces the DES approach to capture the low-level abstraction (i.e., detailed steps/sequence) of the delivery process at the customer's location. Here, three separate DES models (as shown in Fig. 4) were considered for the three customer segments: single-house residents, apartment dwellers, and business/companies. The DES was developed using field observations, practitioner insights, and operational workflow mapping from commercial delivery systems. Within the framework, the DES layer captures sequential operational activities including package arrivals, loading operations, queue dynamics, vehicle dispatching, delivery execution, and completion

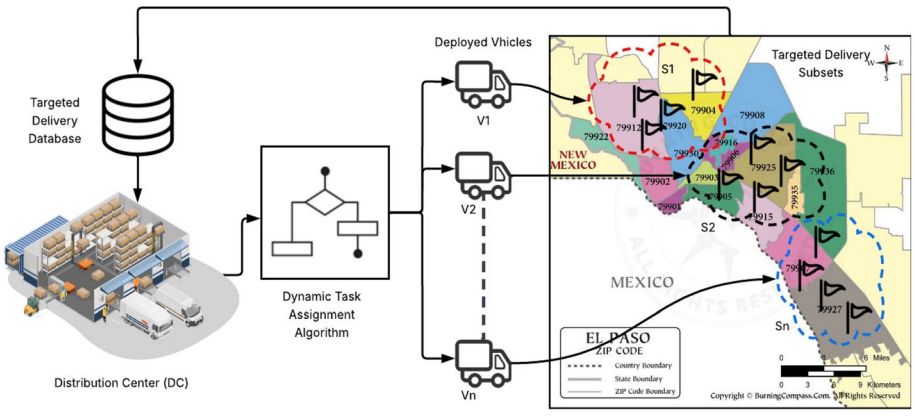

Fig. 3 Schematic Diagram for Agent-Based Modeling (Region-specific Address)

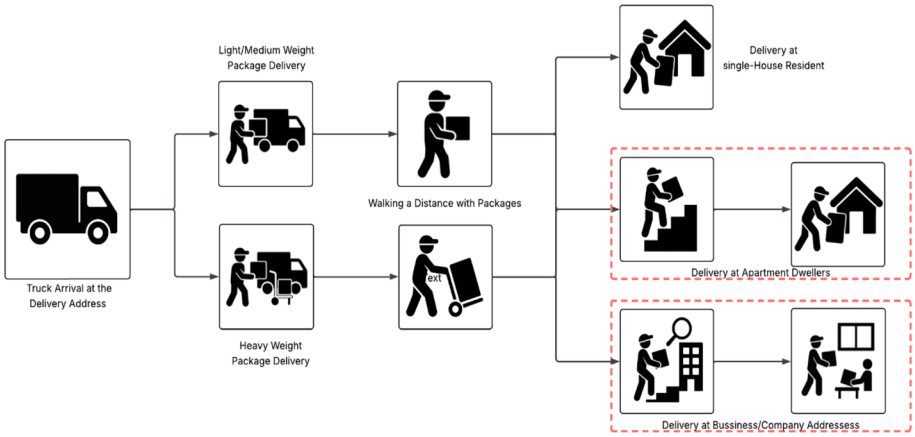

Fig. 4 DES for Low-Level Abstraction in the Delivery End

events. While the standard delivery process is similar, customer segments differ in how they complete the delivery task. For example, in single-house delivery, deliverymen go directly to the house address to deliver the packages. In apartment delivery, the deliveryman must find a specific apartment or building number at the delivery location. Sometimes, the deliveryman needs to walk up a level for a multi-story apartment complex. The process is more complex for business/company delivery locations, as deliverymen may need to access the parking area, walk a distance, go through security to enter the building, and sometimes walk upstairs. The situation becomes more complex when the locations are within a multi-complex and/or secured building or area. In all cases, the delivery process also depends on the type or size of the package, such as whether it is light or heavy. Sometimes the deliveryman needs to use a moving cart and walk a distance to complete the delivery. Taken together, these steps require a meaningful amount of time to ensure that each delivery is completed properly and efficiently. However, accessing time at the micro-level is not trivial. It requires a detailed study, coupled with ergonomics, motion, and time study. Here, we apply the MOST techniques to estimate the time for each detail in DES.

3.3 MOST analysis for LMD

To systematically parameterize micro-level delivery tasks, MOST is used as a standardized, ergonomically grounded time-measurement framework. Rather than relying on assumed or aggregated service times, MOST provides a structured decomposition of manual activities into predefined motion sequences, enabling consistent and replicable estimation of task durations. Each delivery sub-task, such as walking, grasping, placing, or body repositioning, was translated into standardized motion codes and converted to Time Measurement Units (TMUs), then to seconds. Rather than using these deterministic values directly, the observed MOST-derived task times were statistically modeled as triangular distributions representing the minimum, most likely, and maximum task durations. Later, these distributions were inserted within the DES layer to introduce controlled stochasticity, ensuring that service-time variability reflects structured ergonomic analysis rather than arbitrary randomness. This integration establishes a methodological bridge between micro-motion ergonomics and system-level simulation modeling.

For example, A10 indicates moving 10 units. Likewise, if the index is zero (0) next to any letter, then no steps are necessary to complete the task. So, the MOST code for a sequence of "moving 10 units, bending slightly, and placing the package" can be represented as "A10, B3, G1, P0". The sum of the MOST code index values is multiplied by 10 to get the TMU index, which is further multiplied by a factor of 0.036 to convert the TMU into seconds. As such, the TMU index in the above MOST code is 100(14 × 10), which is equivalent to 5.04 (140 ×0.036) s. Using this technique, one can set a precise list of activities and their time standards for delivery activities. It involves lifting packages, placing the box on the cart, going to the door, finding a specific apartment, and interacting with customers (Fig. 5).

To estimate time reasonably, the MOST analysis verifies the index (i.e., the required steps) for each action. The indexed value is directly related to package type (i.e., light/medium/heavy) and delivery location (single-house residence, apartment, and business/office). For example, a heavy package must be handled very carefully, and moving tools may be required, which may increase the delivery time.

Similarly, for an apartment complex and a business/office address, additional time is required to find the specific delivery point. We consider all these factors when determining the index for each task. An illustrative analysis for a lightweight box is demonstrated in Table 3. Ten (10) samples were generated by varying the steps (walking distance) to complete the specific deliveries. Upon completion of the MOST analysis, triangular distributions were estimated for each individual action, as summarized in Table 4.

The MOST is particularly well-suited for logistics applications where direct observation or time-study instrumentation is impractical because of privacy, cost, or access limitations. It was deliberately selected to ensure scientifically grounded micro-level time estimation rather than relying on subjective expert judgment or assumed averages. It provides a systematic, standardized method for estimating task durations using motion elements, allowing delivery activities to be modeled at a small scale and in a repeatable manner. This systematic approach enables consistent workflow without measuring real deliveries, which is useful for analyzing delivery operations in urban areas.

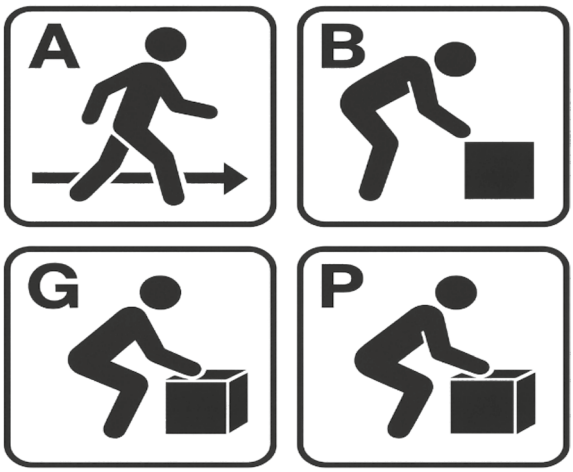

Fig. 5 Common Manual Motion Involved in the End Delivery Process

Table 3 MOST analysis for light delivery

Sample No	Method Step Description (Light Delivery)	Sequence Models (Micro-level Home Delivery)							TMU	Total Time (S)
1 (5–7 steps)	Walk to Box	A 10	B 3	G 1	A 0	B 0	P 0	A 0	140	9.36
	Grab light Box	A 0	B 3	G 1	A 1	B 4	P 0	A 1	120	
2 (11–15 steps)	Walk to Box	A 24	B 3	G 1	A 0	B 0	P 0	A 0	280	14.4
	Grab light Box	A 0	B 3	G 1	A 1	B 6	P 0	A 1	120	
3 (8–10 steps)	Walk to Box	A 16	B 3	G 1	A 0	B 0	P 0	A 0	200	11.52
	Grab light Box	A 0	B 3	G 1	A 1	B 6	P 0	A 1	120	
4 (16–20 steps)	Walk to Box	A 32	B 3	G 1	A 0	B 0	P 0	A 0	360	17.28
	Grab light Box	A 0	B 3	G 1	A 1	B 6	P 0	A 1	120	
5 (21–26 steps)	Walk to Box	A 42	B 3	G 1	A 0	B 0	P 0	A 0	460	20.88
	Grab light Box	A 0	B 3	G 1	A 1	B 6	P 0	A 1	120	
6 (11–15 steps)	Walk to Box	A 24	B 3	G 1	A 0	B 0	P 0	A 0	300	15.12
	Grab light Box	A 0	B 3	G 1	A 1	B 6	P 0	A 1	120	
7 (5–7 steps)	Walk to Box	A 10	B 3	G 1	A 0	B 0	P 0	A 0	160	10.08
	Grab light Box	A 0	B 3	G 1	A 1	B 6	P 0	A 1	120	
8 (8–10 steps)	Walk to Box	A 16	B 3	G 1	A 0	B 0	P 0	A 0	220	12.24
	Grab light Box	A 0	B 3	G 1	A 1	B 6	P 0	A 1	120	
9 (16–20 steps)	Walk to Box	A 32	B 3	G 1	A 0	B 0	P 0	A 0	380	18
	Grab light Box	A 0	B 3	G 1	A 1	B 6	P 0	A 1	120	
10 (21–26 steps)	Walk to Box	A 42	B 3	G 1	A 0	B 0	P 0	A 0	480	21.6
	Grab light Box	A 0	B 3	G 1	A 1	B 6	P 0	A 1	120	

Table 4 MOST analysis time (Sec) results

Variables	Minimum	Maximum	Mode
Light DeliveryP	9.36	21.6	14.2
Hard DeliveryP	10.8	22.32	12.8
leaveConfirm	11.16	24.84	21.96
goToTruck	14.76	28.44	20.52
Parking	24.48	45	40.32
checkAptandDeliver	14.4	28.08	25.2
Register	41.4	81.72	76.68

3.4 Development of hybrid model in computer simulation

The Proposed Hybrid simulations were created using AnyLogic software. As explained in Sect. 3.1 (Modeling the SC Behavior), the truck serves as the main agent to perform the delivery process. The agent is modeled using "`Statechart`" to capture its behavior, including determining the number of deployed trucks, task assignment, and optimal delivery route. For the first stage, we considered thirty different addresses from the El Paso, Texas region and subcategorized them into ten single-family houses, ten apartments, and ten companies. Its GIS feature was used to consider the real-world route of delivery

locations with specific coordinate information (latitude and longitude), as shown in Fig. 6. These coordinates supported spatial analysis, route optimization, and real-time vehicle tracking within the proposed simulation framework.

These addresses are maintained in a database and integrated with the `Statechart` decision logic, as shown in Fig. 7a. Using the `Statechart`, the movement of a vehicle entity is systematically tracked as it progresses through various operational states. The `Statechart` starts with having *n*-Trucks at the Distribution Center (`atDistributor`). This simulation model allows for experimentation by choosing a different number of *n* (deployed truck agents). Once *n* is set, the model dynamically distributes the delivery tasks (as discussed in Sect. 3.1) among the agents (trucks). It subsequently, checks the remaining delivery tasks at each `Branch` (◇ `Branch`) and finds the next delivery addresses using the `findAddress` state based on the shortest path algorithm from the available depots. For example, when a single vehicle is deployed, it collects parcels from the corresponding depot and delivers to all assigned locations; when two vehicles are deployed, the corresponding depot subdivides the delivery addresses into two subsets (as described in Sect. 3.1) and sends the trucks to fulfill the deliveries. The trucks then determine the optimal route plan based on the GIS information. The additional picking and loading time associated with multi-product operations is modeled explicitly within the ABM simulation layer, as shown in Fig. 7. The agent sends a message to the DC after each delivery and proceeds to the next address until it completes all assigned tasks. Subsequently, the `Statechart` changes the state to return the truck to its home location (DC). Notice that while the trucks move to any specific address, the `Statechart` sends the information to the agent about the type of location, as shown in Fig. 7b–e.

With this information, the agents access the corresponding DES model to perform micro-level time analysis of the end-customer delivery process. The DES models all micro-level steps and time considerations, as discussed in Sect. 3.2. The total delivery time is calculated based on the truck's actual transportation time (from the ABM) and the micro-level time analysis from the DES. The actual transportation time is calculated based on the actual distance traveled in miles (access from AnyLogic GIS) and the average agent speed (feet/second). This setup provides a systematic approach to the delivery management system, allowing all pending agents to be tracked and classified for smooth execution in the integrated hybrid model. After integration, a dynamic,

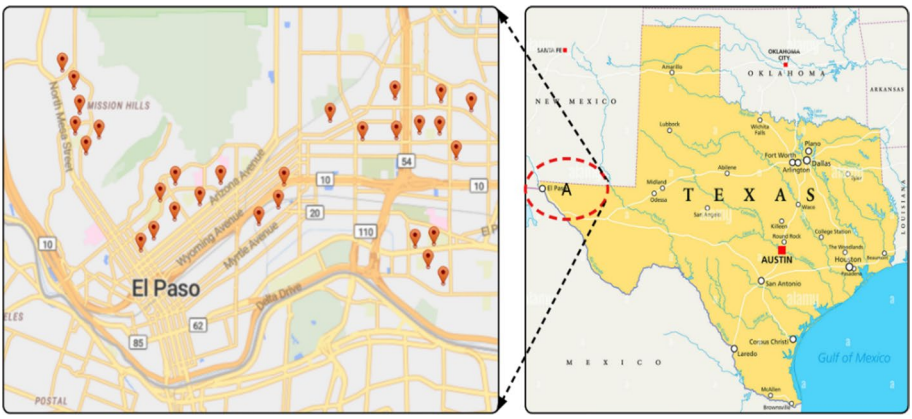

Fig. 6 Accessing Real-World Route using AnyLogic GIS in Agent-Based Simulation

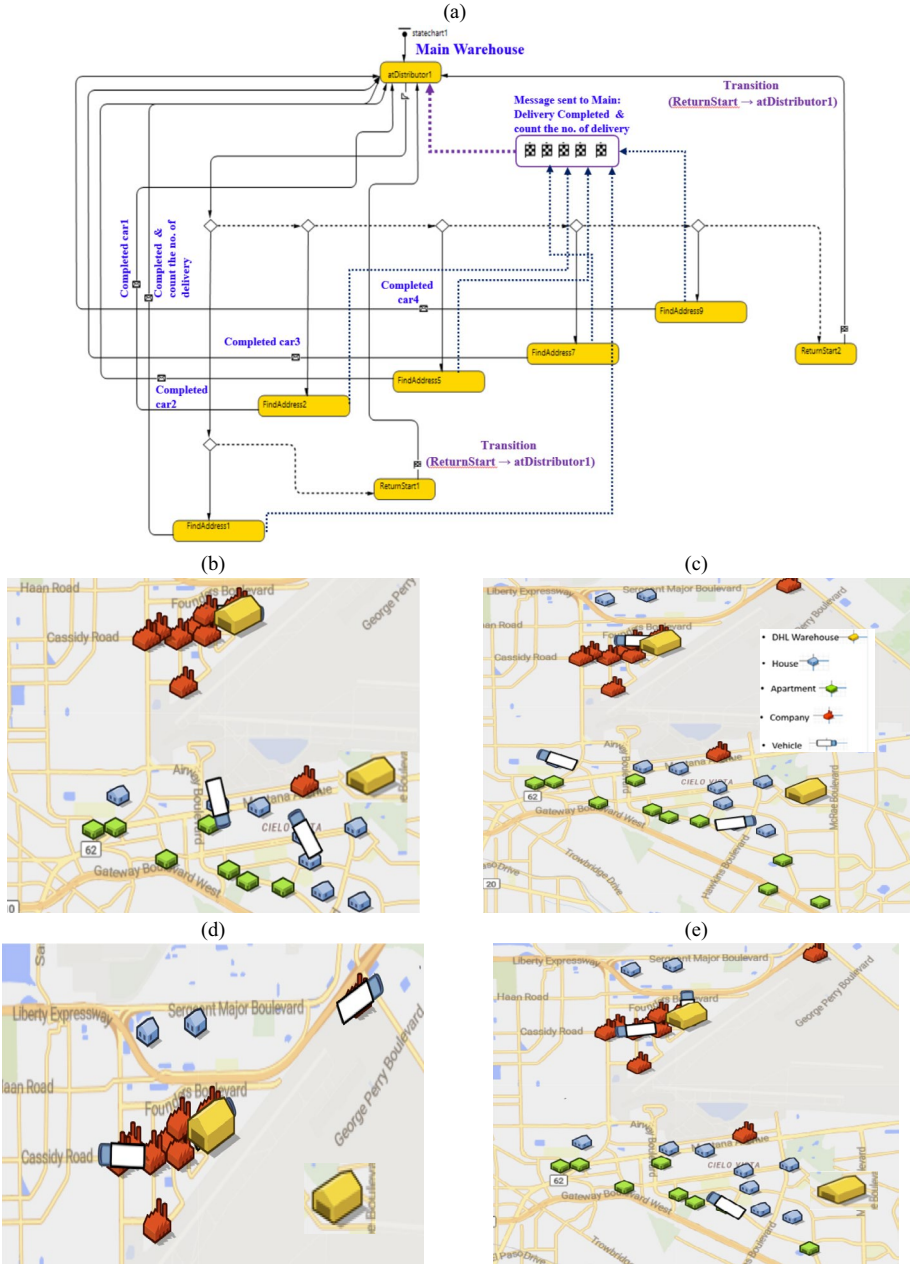

Fig. 7 AnyLogic Statechart to Show Agent-Based Behavior

interactive dashboard is created to gather the required data and display the evaluation metrics shown in Fig. 8. This dashboard enables real-time monitoring, scenario exploration, and performance analysis, facilitating informed decision-making. It illustrates

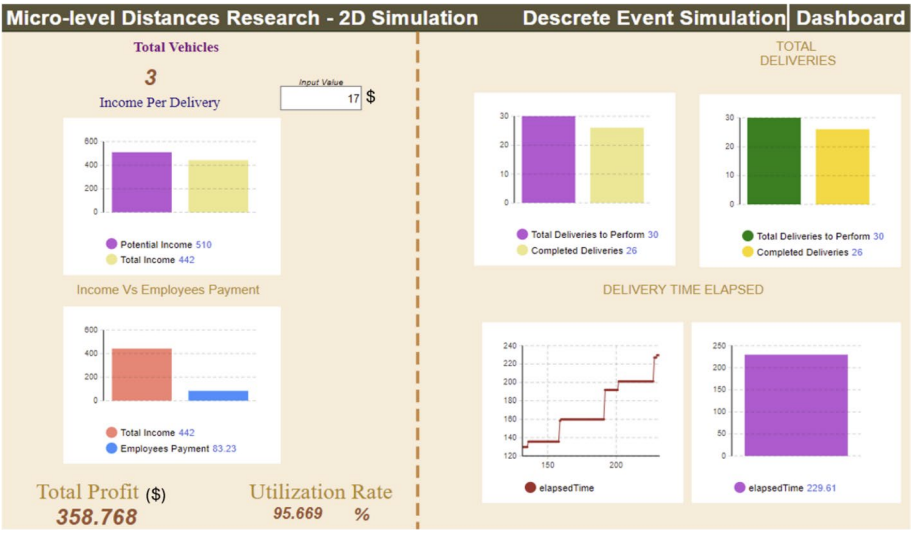

Fig. 8 Dashboard Showing the Evaluation Metrics

the key performance indicators, including total profit, employee utilization rate, elapsed delivery time, and number of completed deliveries.

The dashboard also provides a graphical display of potential income, earned income, truck deployment expenses (employee payments), delivery progress, and elapsed time. It enables decision-makers to intuitively understand the results and turn technical data into business insights.

4 Statistical verification and validation:

This section provides the statistical verification of the proposed LMD simulation model. A single simulation run cannot be considered sufficient because of the inherent randomness in last-mile operations, such as variations in travel times and customer interaction processes. To address this, the proposed hybrid model was tested using a Monte Carlo simulation with 50 trial runs (Fig. 9) to assess the robustness and confidence of the output of delivery time estimation.

As shown in Fig. 10a and b, micro-level tasks add more perturbations at the output end. These include package handling (light/heavy), task times derived from MOST analysis (Table 5), utilization of transporters, and access-related factors (parking delays). The simulation incorporates the uncertainty inherent in these sources via triangular distributions, further increasing the model's realism in capturing delivery dynamics. For example, A triangular distribution $T(3, 5, 4)$ was used for light delivery of packages to houses, while heavy packages were modeled with $T(5, 8, 6.5)$, with average delivery times of 3.499 min and 6.771 min, respectively. For company delivery, registration was modeled with $T(1, 3, 2)$, averaging 2.121 min, while returning to the truck was modeled using $T(2, 3, 2.5)$, resulting in 5.203 min. This means the company's delivery process required extra steps for registration and longer walking distances. The vehicle travel speed was 37 feet/second, and the deliveryman's walking speed was assumed to be 3 feet/second to simulate realistic

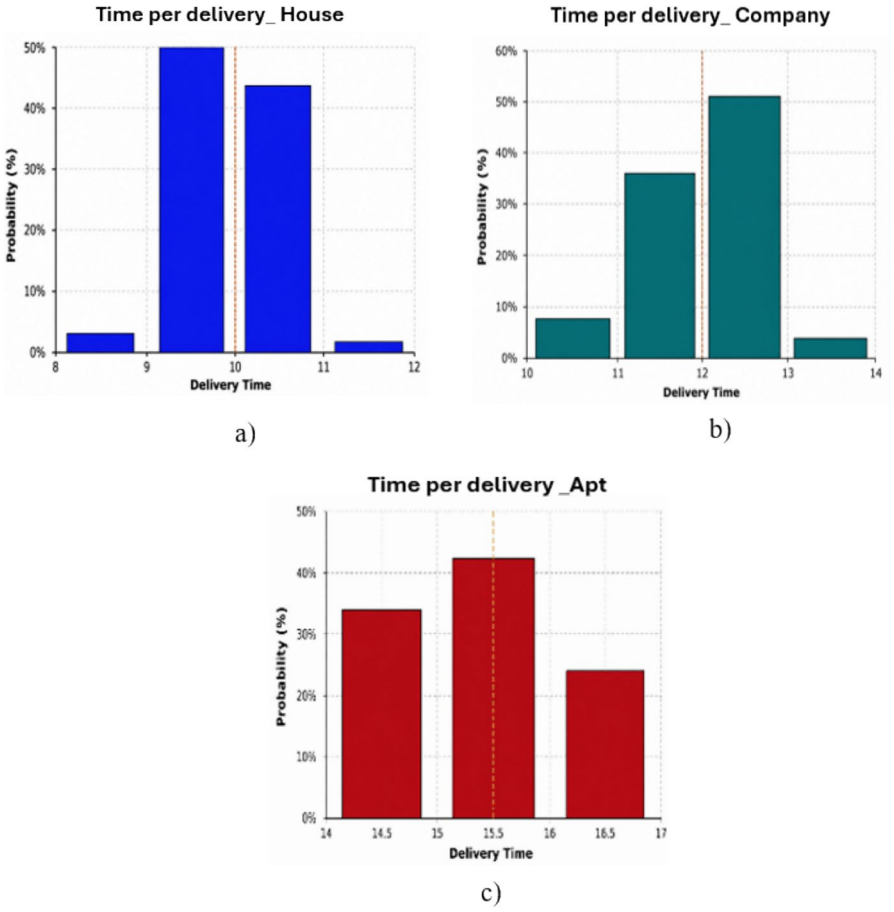

Fig. 9 Fifty Trial Runs for Monte Carlo Simulation

travel times between delivery points. Together, these random parameters and calibrated speed values ensure the simulation accurately reflects operational dynamics and task-specific changes during delivery processes.

The statistics are presented in detail in Table 6 and include the mean, variance, and standard deviation. The deliveries for the house and apartment were low variability (around 0.14 min and 0.10 min respectively). Company deliveries, on the other hand, showed moderate variability (standard deviation of 0.39 min), mirroring realistic aspects such as elevator use and navigating the apartment's interior. The similarity among the simulation replications highlights the robustness of our integrated hybrid modeling approach. The results confirm the effectiveness of our proposed approach in simulating the stochastic nature of the delivery operations and stable performance under different operational conditions. A distributional similarity analysis based on the Wasserstein Distance (also known as the Earth Mover's Distance) is further used to assess the agreement between the simulation results and practical expectations (Panaretos & Zemel, 2019).

A double bootstrap procedure (Negahban, 2025) with 1,000 iterations was used to calculate confidence intervals for the Wasserstein distance values. This provides an additional degree of

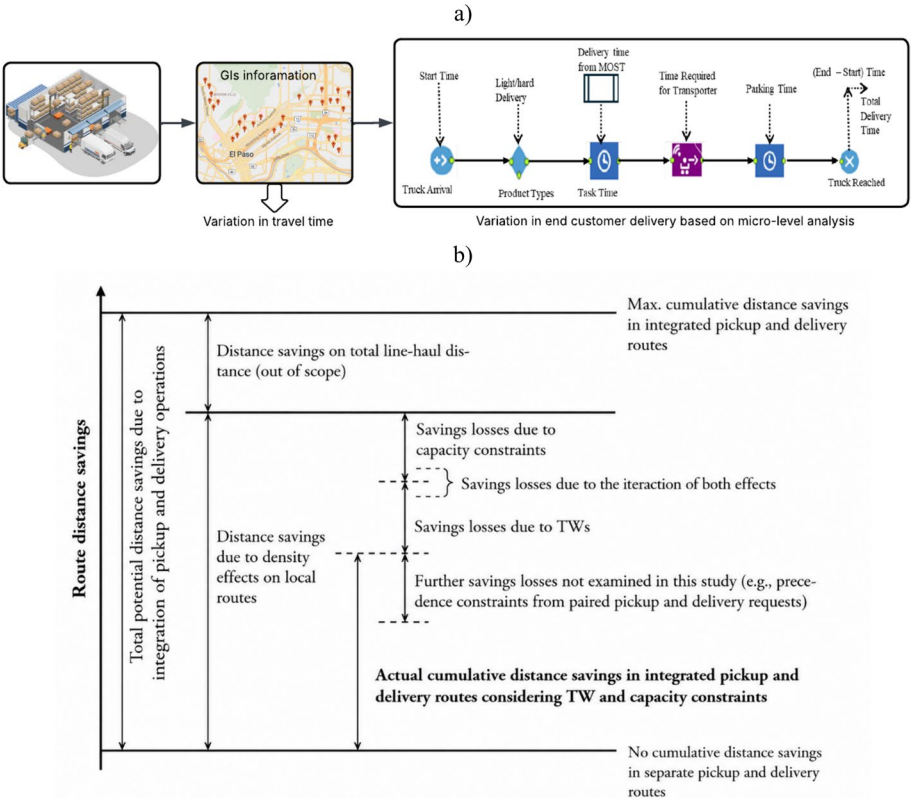

Fig. 10 Sources of variation in the proposed model: **a** process-based time variability and **b** route-saving effects

Table 5 Estimated task completion time for last-mile delivery

Parameter	Types of Destination	Trianguler distribution T (min, max, mode)	Value from Monte Carlo Run (minutes)
lightDeliveryP	House/Home	T (3,5,4)	3.499
hardDeliveryP		T (5, 8, 6.5)	6.771
leaveHomeConfirmP		T (2, 3, 2.5)	2.475
lightDeliveryP1	Apartment	T (3, 5, 4)	4.192
hardDeliveryP1		T (5, 8, 6.5)	6.046
checkAptandDeliverHd		T (10, 15, 12)	12.456
checkAptandDeliverLt		T (2, 7, 5)	5.671
lightDeliveryP2	Company	T (1.5, 2.5, 2)	1.912
hardDeliveryP2		T (2, 3.5, 3)	2.834
goToTruckP3		T (2, 3, 5.5)	5.203
RegisterP		T (1, 3, 2)	2.121

Table 6 Summary of delivery time variability across delivery types

Delivery Type	Time Range (min)	Mean Time (min)	Variance (s^2)	Standard dev. (min)	Observations
House	10.0 – 11.0	10.3	0.02	0.14	Low variability
Company	11.0 – 12.5	11.9	0.15	0.39	Medium variability
Apartment	15.4 – 15.6	15.5	0.01	0.1	Low variability

statistical reliability. The Wasserstein Distance ($\widehat{W}$), as formulated in Eq. (1) is widely used as a distance metric between probability distributions in optimization, probability, and statistics. In general, it is the minimum amount of effort needed to convert one distribution to another. It is a valuable indicator for comparing distributions and assessing the model's real-world behavior.

$$\widehat{W} = \frac{1}{n}\sum_{i=1}^{n}\left|x_{sim}^{(i)} - x_{theory}^{(i)}\right| \tag{1}$$

where, $x_{sim}^{(i)}$ is the sorted values of the simulated data. And $x_{theory}^{(i)}$ is the sorted values of the MOST-based (time study) data, n is the number of samples.

The $\widehat{W}$ quantifies the difference between the simulated delivery-time distributions and the practical MOST-based estimates. Lower values of $\widehat{W}$ indicates higher similarity and greater model accuracy. The range of the true Wasserstein Distance, represented by the 95% Confidence Interval (CI), gives an indication of the trustworthiness and reliability of the calculated result, as shown in Table 7. The moderate distance of 0.442 and narrow CI (0.342,0.548) for house delivery suggest that the simulation performs well in this simple, consistent scenario and matches the MOST-based estimates closely.

For company deliveries, the observed $\widehat{W}$ of 1.278 with a narrow CI (1.212, 1.345) indicates stable results in the current analysis.

We also statistically checked the external plausibility for the MOST-derived estimated times and compared them with a recently published real-world LMD dataset (Vrani et al., 2025). It includes the times for the 79 delivery locations. The published data provide an average service time of 4–12 min for heterogeneous urban conditions. Figure 11 compares the empirical distribution with our MOST-based estimates. It shows that delivery times for houses fall in the lower range of the reported empirical values, while delivery times for companies are at the top of the quartiles due to additional access procedures. Note that our MOST analysis-based data vary from the published data. This difference stems from our method of categorizing time by individual delivery point, whereas the published data reports time averaged across delivery points. The apartment deliveries exceed some benchmark observations in our model. This is because it explicitly represents multi-story access, corridor travel, elevator waiting, and controlled-entry processes that conventional datasets often aggregate. This empirical

Table 7 Distributional similarity analysis using wasserstein distance

Delivery Type	$\widehat{W}$	Confidence Interval (95%)
House	0.442	(0.342, 0.548)
Apartment	0.275	(0.148, 0.462)
Company	1.278	(1.212, 1.345)

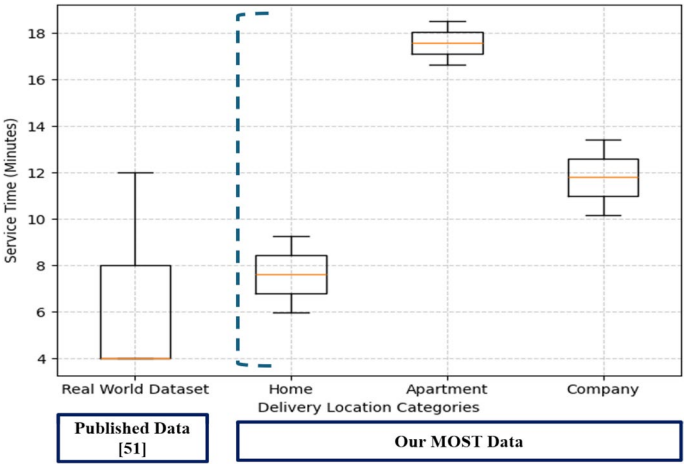

Fig. 11 Data Validation: Real World vs Proposed MOST Analysis

foundation validates the applicability and suitability of our estimated service times for policy-driven experimentation with different fleet sizes, routing, and depot setups in real delivery operations.

For the service times derived from MOST, we conducted 150 Monte Carlo runs, producing 50 for each of the three destination types (House, Apartment, and Company deliveries). One-way ANOVA and pairwise independent t-tests were also used to statistically validate these samples.

This was confirmed by the ANOVA results ANOVA($F(2,147) = 1152.66, p < 0.001$). The mean service time for apartment deliveries was 17.6 min, the highest among the three delivery types. For houses, it was 7.6 min, and for companies, it was 11.8 min, as shown in Table 8. Table 9 also showed that house vs. apartment and apartment versus company deliveries differed significantly. This confirms that the navigation complexity (i.e., longer travel distance and accessibility constraints, especially in multi-storied apartments) is the primary reason for longer service time. Furthermore, Fig. 12 presents the sensitivity analysis results (Appendix 3 in the supplementary file) for deviations in MOST task durations between -20% and $+20\%$. The results consistently indicate that 'apartment deliveries' is the most time-consuming service type across all scenarios, reflecting the strength of the micro-level service. We then incorporated these validated service-time distributions into the proposed simulation framework and compared them with existing simulation- and optimization-based routing methods.

Table 8 Monte carlo summary statistics for MOST-based service time validation across delivery types

Destination Type	Number of Replications	Mean (min)	Std. Dev	Minimum	Maximum	95% CI
House	50	7.6	1.19	6	9.2	[7.26, 7.94]
Apartment	50	17.6	0.67	16.6	18.5	[17.41, 17.79]
Company	50	11.8	1.19	10.2	13.4	[11.46, 12.14]

Table 9 Pairwise statistical comparison of service times across delivery destination types

Comparison	t-statistic	p-value	Interpretation
House vs Apartment	-51.78	< 0.001	Mean delivery time is significantly longer for apartments than for houses
House vs Company	-17.65	<0.001	Mean delivery time is significantly longer for Company than for houses
Apartment vs Company	30.03	< 0.001	Mean delivery time is significantly longer for apartments than for companies

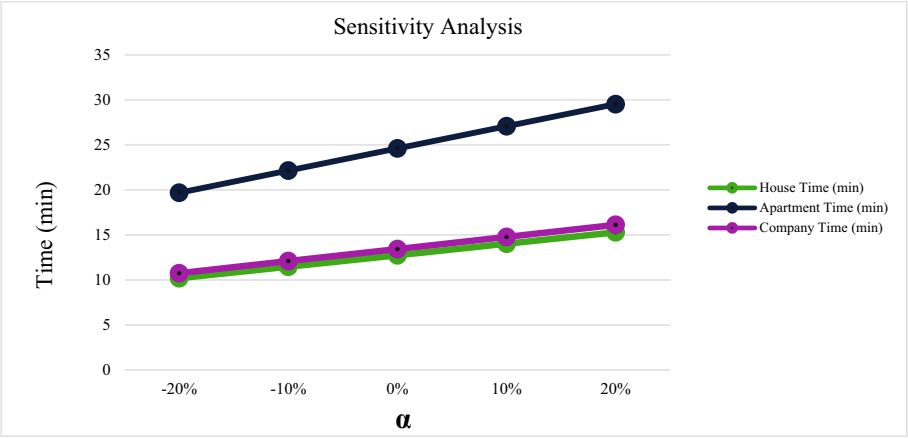

Fig. 12 Sensitivity Analysis of MOST-Based Task Time Variations Across Delivery Categories

5 Results and discussion

This section evaluates the outcomes of four analytical approaches across varying fleet sizes to address our research objectives. Specifically, we thoroughly analyzed and compared these scenarios: (1) Micro-level analysis, (2) Macro-level simulation (existing simulation), (3) MILP-VRP optimization (Appendix 5), and (4) heuristic ALNS optimization (Appendix 4). The existing approach (macro/traditional) estimates delivery service times using aggregate assumptions derived from expert judgment or historical averages, which simplifies modeling but often overlooks location-specific variability and operational complexities. In contrast, the proposed micro-level framework uses detailed GIS-driven task decomposition and MOST-based service modeling to estimate delivery times. For additional validation, we benchmarked the proposed framework against an exact MILP-VRP model and a heuristic ALNS approach, both widely used for routing optimization. These results serve as a reference for conventional routing techniques, which mostly rely on distance minimization and route feasibility.

Table 10 (also shown in Fig. 13) summarizes the comparative results for fleet sizes from one to five vehicles. In the single-vehicle case, the proposed micro-level analysis made 14 deliveries, which demonstrates better performance than Macro (12), MILP-VRP (12), and ALNS (11). The micro model also achieved a lower penalty ($19.2, assuming a $1.2 penalty cost per missing delivery) and higher utilization (97%) than ALNS ($22.8). For instance, in the two-vehicle case, MILP-VRP completed the most deliveries (21) because it optimizes delivery routes. Whereas the micro model completed 18 deliveries. However, the MILP required significantly more computational time (10.5 min) than the micro model (0.5 min), highlighting the trade-off between solution optimality and computational scalability. While ALNS delivered 19 packages and took much less time (0.5 min), its utilization was lower than the micro model. The micro-level analysis for the 3-vehicle configuration made 27 deliveries, outperforming macro (21), MILP-VRP (25), and ALNS (26), with 3 missed deliveries and a low penalty cost of $3.6. This makes it clear that micro-level task sequencing uses resources more efficiently because it provides more accurate service times. ALNS achieved full delivery completion (30 deliveries) with zero penalties in the four-vehicle scenario, whereas both the micro-level analysis and MILP-VRP completed 29

Table 10 Operational performance comparison of routing and simulation models under different vehicle deployment scenarios

Vehicle No	Model	Delivery Completed	Delivery Missing	Total Elapsed Time (Min)	Utilization Rate (%)	Missing Penalty ($)
1	Macro (traditional)	12	18	239	98	21.6
	MILP-VRP	12	18	235	97.4	21.6
	ALNS	11	19	222	93	22.8
	Micro (Ours)	14	16	234	97	19.2
2	Macro (traditional)	16	14	234	97	16.8
	MILP-VRP	21	9	239	98.9	10.8
	ALNS	19	11	222	86.9	13.2
	Micro (Ours)	18	12	237	97	14.4
3	Macro (traditional)	21	9	240	98	10.8
	MILP-VRP	25	5	236	98.3	6
	ALNS	26	4	236	87.5	4.8
	Micro (Ours)	27	3	233	98	3.6
4	Macro (traditional)	28	2	229	95	2.4
	MILP-VRP	29	1	230	93.8	1.2
	ALNS	30	0	223	89.5	0
	Micro (Ours)	29	1	223	93	1.2
5	Macro (traditional)	30	0	216	90	0
	MILP-VRP	30	0	185	76	0
	ALNS	30	0	195	65	0
	Micro (Ours)	30	0	157	70	0

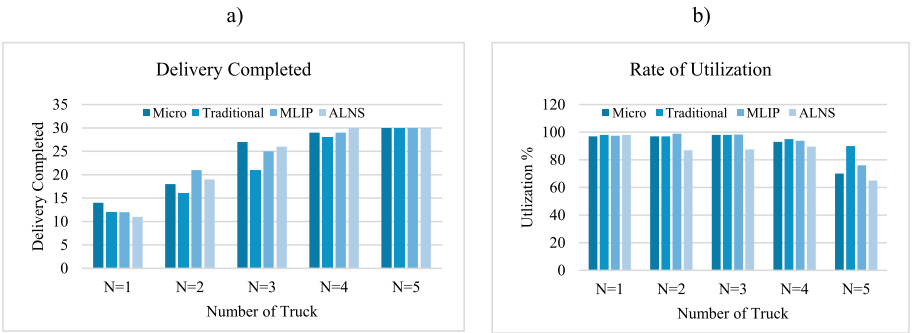

Fig. 13 Output showing the comparative analysis: **a** delivery completed, **b** utilization rate

deliveries. All approaches completed the targeted 30 deliveries using the 5-vehicle configuration. The existing model, by contrast, outperformed the other three models with the lowest total elapsed time (157 min), with more efficient operations due to reduced idle time and faster task completion.

These results give some remarkable findings. Firstly, the optimization models (MILP-VRP and ALNS) perform well at maximizing the number of completed deliveries,

especially when the fleet size is medium. MILP, however, has much higher computational demands because of the combinatorial nature of routing decisions, and ALNS sacrifices some operational realism to execute routing decisions quickly. Second, the proposed micro-level analysis consistently shows high operational efficiency, maintaining its success not only by competing with optimization benchmarks but also by adding operational practicality. This approach explicitly accounts for parking delays, walking distance, time required to enter the apartment, security measures, variability in handling parcels, and different pickup operations in the depot, compared with traditional VRP formulations that consider only deterministic service times and optimize route distance. These micro-level operational details explain why the proposed model is sometimes more efficient in elapsed time than both traditional simulation & MILP, while delivering competitive completion rates.

The proposed approach also aligns with the concept of a data-informed simulation in logistics systems. It integrates real-world spatial data (GPS-based distances, delivery locations), operational processes, and stochastic service-time behavior into a virtual environment for experimentation and decision support. By combining GIS-based routing, MOST-derived service-time modeling, and agent-based decision logic, the framework captures both structural and behavioral aspects of last-mile operations. It allows assessment of fleet sizing, depot assignment, and routing policies under realistic uncertainty, extending beyond classical deterministic VRP models. From an operations research perspective, the LMD problem addressed in this study is a stochastic, time-dependent extension of the classical VRP.

Unlike traditional VRP formulations that assume deterministic service times, this study models service processes as stochastic variables derived from ergonomics-based MOST analysis. This formulation introduces endogenous variability into routing decisions, aligning the problem with stochastic VRP and simulation–optimization frameworks. Thus, this framework can be interpreted as a hybrid simulation–optimization model, where optimization logic (shortest-distance routing and task assignment) is embedded within a discrete-event, agent-based simulation environment. Rather than solving a deterministic routing problem in a single step, the model evaluates system performance under multiple stochastic realizations of service times and operational conditions. This aligns with simulation–optimization approaches commonly used in complex logistics systems where analytical solutions are intractable.

6 Conclusion

This work presents a simulation-based hybrid framework for applying micro-level route optimization to urban delivery logistics. It combines GIS-integrated DES and ABM with MOST to capture detailed variability in delivery tasks that traditional routing models typically ignore. It can also analyze delivery performance, pinpoint operational inefficiencies, and measure the impact of vehicle deployment decisions without interfering with real-world operations. This research primarily integrates micro-level service-time estimation, dynamic task assignment, GIS-based routing, and experimentation to identify an effective approach to improve delivery completion, reduce penalties, and increase vehicle utilization. To strengthen the methodological contribution, we compared it with exact MILP-VRP optimization and heuristic ALNS approaches. The comparative results showed that the proposed micro-level framework, in most cases, performed well in operational performance, with a significant reduction in computational time compared to exact optimization

techniques. Integrating Monte Carlo simulation and Wasserstein distance-based double bootstrap validation further improved the model's robustness by capturing service-time variability and statistically validating simulation outputs. This structure allows businesses to adapt quickly to operational changes while maintaining efficient delivery performance. Future research could extend this model to include environmental conditions such as traffic, weather, fuel emissions, real-time demand fluctuations, and vehicle failures to better reflect real-world operational uncertainty. Also, the current framework does not explicitly solve large-scale MILP models for global route optimization or directly integrate ALNS within the simulation loop. Future studies can explore exact optimization, metaheuristic routing, real-time demand arrivals, and AI-driven adaptive routing strategies to further improve scalability and operational responsiveness.

7 Managerial implications

The last-mile delivery sector continues to face increasing pressure from rising customer expectations, labor shortages, fuel costs, and service reliability requirements. The logistics expenses of last-mile operations have been found to be about 13–75% of the total logistics expenses in previous studies, which makes operational efficiency a critical managerial concern (Gevaers et al., 2014). In this context, the proposed framework provides operational-level decision support through actionable logistics management decisions. Firstly, the outcomes provide clear guidelines on how to deploy fleets. For instance, under the current demand structure in our experiments, 1 or 2 vehicles lead to higher missed deliveries and less profit. However, increasing the fleet size can improve service performance to an optimal level. Managers can use this framework to identify the point at which additional vehicles increase value and where they become underused. Second, the model can support cost–benefit analysis beyond standard routing outputs. Managers are not limited to minimizing travel distance; they can also consider trade-offs between labor utilization, missed-delivery penalties, delivery completion rates, and service efficiency. For example, apartment deliveries always took longer because of parking issues, moving vertically, and the time it took for the customer to access the space. This may indicate that managers should consider dedicated drivers, flexible delivery times, or reconfiguring apartment delivery areas. Third, the framework enables organizations to assess implementation challenges before real-world deployment. Organizations often struggle to implement GPS tracking, collect accurate service-time data, and align the dispatch, driver, and routing functions. Our simulation environment lets companies test policies before committing to purchasing extra vehicles, routing software, or hiring more employees. Furthermore, the model can support scenario planning for typical disruption events, including traffic, order volume variations, and labor shortages. Managers can test different routing options and resource allocation settings in a risk-free environment before deployment. Finally, it provides a "how-to" path to digital transformation of the delivery system by combining GIS routing, operational simulation, and historical delivery data in a single decision-support environment. This enables logistics companies to shift from fixed delivery plans to more flexible, data-driven delivery operations.

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Data availability The datasets used and/or analyzed during the study are available from the.corresponding author upon request.

Declarations

Conflict of interest The authors declare that they have no known conflict of interest that could.have appeared to influence the work reported in this paper.

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