An Innovative Urban Delivery System Based on Customer-Selected Addresses and Cost-Effective Driver Rates

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Abstract: Last-mile delivery is undergoing rapid transformation due to the surge in home delivery services and the increasing demand for convenience, driven by the digitalization of businesses. In response to this evolving landscape, businesses are exploring innovative delivery methods, including the use of parcel lockers and drone delivery. This study investigates a novel approach to last-mile delivery, utilizing non-professional delivery personnel (crowd-shippers) to fulfill customer orders at designated addresses. By leveraging crowd-shippers and considering service locations alongside a comprehensive set of drivers' preferences—including familiarity with the delivery area, traffic conditions, and ease of access— our aim is to minimize unsuccessful delivery attempts, reduce costs, and align with environmental and societal sustainability goals. The main objective is to minimize the total cost of delivery, accounting for both the total distance traveled and the drivers' preferences regarding delivery points. We develop and solve a mixed-integer programming model that represents this scenario, providing insights into the advantages of integrating drivers' preferences into last-mile delivery optimization strategies.

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1 INTRODUCTION AND LITERATURE REVIEW

The field of logistics encompasses various sub-areas, each with distinct characteristics. Urban logistics, a subset, focuses specifically on the challenges and opportunities related to managing the flow of goods in urban environments. Its primary goal is to optimize the supply chain in urban areas, emphasizing efficient goods delivery, especially during the last mile, which is a crucial aspect of urban logistics, referring to the final phase of delivery, from the distribution center to the end consumer. Last-mile delivery (LMD) is the final stage of the distribution process, where the shipment is transported from the last distribution hub—such as a warehouse or distribution center—to the recipient, whether at their home or at a nearby collection point. This process is gaining momentum due to the exponential growth of e-commerce (Tilk et al., 2021) and urbanization (Amaral and Cunha, 2020). This urbanization trend is projected to increase the urban population by almost 600 million by 2030, reaching 5.2 billion , and further to 9.7 billion by 2050 (United Nations, Department of Economic and Social Affairs, Population Division, 2022). This surge in urban population emphasizes the need for effective last-mile solutions to meet the growing demand for delivery services. However, it also presents challenges such as environmental impact, high costs, service quality, and returns management ((Kiba-Janiak et al., 2021),(Pahwa and Jaller, 2022)). In the first quarter of 2023 in Morocco, merchant sites and Interbank Electronic Payment Center (CMI) affiliates witnessed substantial growth in online payment transactions, totaling 2.9 billion dirhams (or a 32.3% increase compared to the same period in 2022). Recently, in early 2021, Amazon launched a challenge, in collaboration with the Massachusetts Institute of Technology's (MIT) Center for Transportation & Logistics, which aimed to improve the efficiency of freight delivery by integrating driver expertise into optimization models. Three research teams won a total of $175,000

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in prize money for their innovative route optimization models in the Amazon LMD Research Challenge.

In light of these advancements, the main objective of this study, conducted as part of a research project on logistics and urban mobility, is to address the need for optimizing the LMD Problem (LMDP) with consideration for service options and drivers' preferences.

The Vehicle Routing Problem (VRP) and its various extensions have garnered significant attention in academic literature. Foundational texts such as (Toth and Vigo, 2002), (Golden et al., 2008), and (Toth and Vigo, 2014) provide comprehensive insights into the topic, while extensive literature reviews can be found in works like (Cordeau et al., 2002), (Eksioglu et al., 2009), (Laporte, 2009), and (Vidal et al., 2020).

The initial studies addressing both location and routing dimensions can be traced back to the 1960s, with notable contributions from authors such as (Von Boventer, 1961), (Webb, 1968), and (Watson-Gandy and Dohrn, 1973). Since then, a diverse array of problems has emerged, each integrating routing and location decisions, as highlighted in the survey by (Prodhon and Prins, 2014). More recent works have explored variations like the Swap-Body VRP (SB-VRP), where trucks and semi-trailers are used to minimize total costs while managing complex constraints related to customer accessibility and vehicle type (Todosijević et al., 2017). Similarly, VRPs have been applied in logistics contexts involving truck scheduling, where the goal is to optimize outbound deliveries by minimizing total operation time, as seen in (Benmansour et al., 2024), which focuses on dispatching trucks from a central terminal to serve dispersed customers efficiently.

As society evolves toward a shared economy, the role of Occasional Drivers (ODs) in crowdshipping is anticipated to become increasingly prominent in future delivery systems. In crowdshipping, individual ODs operate as resource providers in the sharing economy, offering their vehicles and time to assist with LMD tasks, as discussed in (Strulak-Wójcikiewicz and Wagner, 2021). It is noteworthy that many companies have integrated crowdshipping into their business models since 2011, a trend significantly accelerated by Amazon's involvement starting in 2015 (Jazemi et al., 2023). A key advancement in this area is the introduction of the VRP with Occasional Drivers (VRPOD) by (Archetti et al., 2016). This variant combines traditional vehicle resources with the capabilities of ODs, exploring various compensation schemes to enhance operational efficiency. The findings from (Archetti et al., 2016) indicate that incorporating crowdshipping systems can yield more effective delivery solutions. Further developments in VRPOD include the work of (Macrina et al., 2017), which added time window considerations, resulting in the VRPOD with Time Windows and Multiple Deliveries (VRPODTWmd). This version requires that each customer be associated with specific time frames for receiving packages, allowing ODs to execute multiple deliveries in a single trip. While some studies have concentrated on drivers' behavior and their willingness to serve as crowd-shippers (e.g., (Al Hla et al., 2019)), others have adopted innovative methodologies. For instance, (Torres et al., 2022b) proposed a two-stage stochastic framework to address a stochastic variant of VRPOD, acknowledging uncertainties in ODs' availability. Their model addresses the challenges associated with deliveries requiring customer signatures, which may necessitate returning items to the depot. The authors implemented a branch-and-price algorithm to solve the problem precisely, alongside a column generation heuristic for larger instances. Moreover, (Torres et al., 2022a) introduced a framework wherein the destinations of ODs are not predetermined. They modeled route duration constraints to enhance ODs' willingness to accept delivery routes, aiming to keep them manageable. This extension of their previous model (Torres et al., 2022b) focused on minimizing both fixed and variable compensations paid to ODs and employed branch-and-price algorithms as well as rapid heuristics for handling larger datasets.

The concept of the VRP with Delivery Options (VRPDO) has also emerged over the past two decades, gaining traction in LMD optimization. This problem extends traditional vehicle routing models by considering various delivery options available to customers, such as multiple delivery locations or preferences regarding timing. The pioneering work of (Cardeneo, 2005) first addressed the challenge of accommodating multiple potential delivery addresses within the VRPDO framework. Recently, (Tilk et al., 2021) tackled the VRPDO, allowing shipments to be directed to alternative locations with varying time windows while also factoring in customers' preferences for different delivery options. They proposed a branch-price-and-cut algorithm to solve this complex optimization issue. Delivery to optional points has rapidly gained popularity in the realm of LMD, driven by customers' desire for timely and reliable service. Customers can provide multiple potential delivery points along with time windows, enabling the delivery plan to select the most suitable option. Earlier research often overlooked customer preferences regarding delivery locations (e.g., (Anily, 1996)), whereas more recent studies have expanded the scope to include customer preferences in route planning (e.g., (Pourmohammadreza and Jokar, 2023)).

In an effort to balance route cost minimization with customer satisfaction, which increasingly demands flexibility in product delivery, (Los et al., 2018) introduced a Generalized Pick-up and Delivery Problem (GPDP) that incorporates Time Windows and Preferences (GPDPTWP). Their evaluations demonstrated a 30% improvement in objective function values through the use of both exact and approximate methods. Following this, (Dragomir et al., 2022) explored the PDP with alternative locations and overlapping time windows, seeking to optimize transportation requests with a fleet of vehicles. They considered multiple pickup and delivery locations, including alternate recipients, and assessed the feasibility of utilizing 24-hour locker boxes. Their solution approach involved a multi-start adaptive large neighborhood search with problem-specific operators. For a comprehensive overview of VRPs specifically related to LMD in urban contexts, refer to (Jazemi et al., 2023).

This paper introduces a variant of the VRPDO that incorporates an additional constraint: Drivers' Preferences. The study focuses on drivers' preferences, considering multiple factors that influence the assignment of delivery routes. Rather than relying solely on distance, the model incorporates a broader range of driver-related preferences, which are captured through the parameter β (see Section 2.1 for a detailed explanation). By accounting for these factors, the model aims to enhance the efficiency of LMD operations. This approach improves service quality by optimizing routes based on practical preferences, ensuring deliveries are carried out under more favorable conditions for the drivers. To the best of our knowledge, this study is the first to address the LMDP while simultaneously considering both service options and a comprehensive set of driver preferences (cf. (Jazemi et al., 2023)). The primary objective is to address practical challenges in online item deliveries, particularly for customers requiring multiple deliveries within the same day, by ensuring that drivers' routes are optimized for both efficiency and quality. This is achieved by incorporating drivers' preferences into the routing process, thereby improving both service performance and delivery conditions.

The main contributions of this paper are as follows:

- We propose a novel Mixed Integer Programming (MIP) formulation designed to address the LMDP. Our model incorporates service options and drivers' preferences, offering a new perspective on optimizing LMD with non-professional delivery personnel (crowd-shippers).
- We extend the traditional LMD framework by explicitly considering drivers' preferences related to minimizing travel distance. This innovative approach aims to reduce delivery costs and increase efficiency by aligning drivers' preferences with route optimization.
- We provide a comprehensive numerical analysis of our proposed model, demonstrating its practical effectiveness through computational experiments, with results achieved within reasonable computing times.

The remaining sections of this paper are organized as follows. Section 2 formally presents the problem addressed in this study and provides an illustrative example of a feasible solution. Section 3 introduces a novel MIP model developed for solving the problem. Experimental results of the MIP formulation are investigated in Section 4. Finally, Section 5 concludes the paper by summarizing the findings and discussing future perspectives.

2 PROBLEM DESCRIPTION

This section provides a comprehensive overview of the LMDP with service options and drivers' preferences. The first part formally describes the problem, while the second part presents an illustrative example to demonstrate a feasible solution to the problem.

2.1 Formal Problem Definition

We consider a central depot, denoted by index 1, from which all deliveries originate. In an urban area, there is a set of clients $\mathcal{N} = \{2, 3, \ldots, n\}$, each of whom must be served from the depot. For each client $i \in \mathcal{N}$, two potential delivery locations are available: a primary address (e.g., home) and an alternative address (e.g., work), and the delivery must occur at one of these suitable locations. Additionally, there is a set $\mathcal{V}$ of m delivery vehicles responsible for completing these deliveries. The central depot, the main addresses, and the alternative addresses constitute a set of nodes denoted by Ω. The main and alternative address of client i ($2 \leq i \leq n$) are represented by the pair of nodes $(i, i+n-1)$.

The delivery route planner aims to minimize the parcel provider's costs by assigning each driver to clients in a way that aligns with their preferences. In this model, the parameter $\beta_{k,i}$ plays a crucial role in capturing the drivers' preferences, allowing the provider to optimize the assignment of delivery points

Table 1: Notations.

Sets and Indices	
m	number of vehicles available
n	number of nodes representing the depot and the main addresses of customers
n'	number of clients ($n' = n - 1$)
$\mathcal{V}$	set of vehicles available $(1, 2, \ldots, k, \ldots, m)$
$\mathcal{N}$	set of clients main location $(2, 3, \ldots, i, \ldots, n)$
Ω	set of nodes $(1, 2, \ldots, 2n - 1)$
Parameters	
$d_{i,j}$	distance between node i and node j
α_k	the price to be paid to the driver of vehicle k for each distance unit
$\beta_{k,i}$	the price to be paid for each delivery of vehicle k to serve node i
Decision variable	
$x_{i,j,k}$	binary variable that equals 1 if vehicle k goes from node i to node j. 0 otherwise
$y_{k,i}$	binary variable that equals 1 if node i is served by the vehicle $k \in \mathcal{V}$. 0 otherwise
u_i	positive integer variable representing the sequencing of nodes

while maintaining efficiency. Specifically, $\beta_{k,i}$ represents the cost incurred when the driver of vehicle k serves client i. This cost takes into account various parameters, such as the driver's familiarity with the neighborhood where client i is located, the ease of circulation in that area (traffic density, terrain slope, road conditions, etc.), as well as the proximity to the driver's workplace. Thus, the more these factors increase the complexity of the delivery, the higher the cost $\beta_{k,i}$, indicating a lower preference for assigning this client to the driver of vehicle k. This framework captures a real-world scenario where the manager prefers routes that minimize the overall travel distance while respecting drivers' preferences by aiming for minimal operational costs. This is further facilitated by delivery flexibility, as each customer has two addresses instead of just one. Moreover, the parameter α_k is used to denote the payment to the driver of vehicle k for each unit of distance traveled. Although α_k does not directly influence driver preferences, it ensures compensation for actual travel distances, offering a financial incentive for efficient routing aligned with those preferences. It is essential to clarify that the terms vehicle k and driver k are used interchangeably in this paper.

In practice, the items ordered online are generally small in size, allowing non-professional drivers to manage deliveries using their own modes of transport, which should ideally be environmentally friendly in an urban setting. As the day begins, all items and delivery vehicles are gathered at the depot, ready for distribution. The items designated for delivery have been prepared and packaged in advance, often the day before, particularly considering that they were ordered online. Each vehicle $k \in \mathcal{V}$ must make a delivery tour, starting from node 1 and traversing a set of clients, including their primary or alternative addresses. The distance between two consecutive nodes i and j visited by the same delivery vehicle k is denoted as $d_{i,j}$. Upon completing their delivery routes, vehicles return to the depot, a step essential for overall operational efficiency. This allows for the collection of delivery receipts or signed documents from clients for record-keeping and compliance. Additionally, the return provides a centralized point for managing the process, ensuring deliveries are tracked and crowdshippers are prepared for the next round. Additionally, we assume, without loss of generality, that each client i must be delivered to either their main address or their alternate address by a single delivery vehicle. Furthermore, we assume that time windows are not considered and that the capacity of each vehicle is sufficiently large, given the small size of the products typically ordered online.

The primary objective is to minimize the total cost of delivery, which includes the distance traveled by vehicles, as well as considerations related to drivers' preferences for more efficient route assignments. This includes factors such as familiarity with the area, traffic conditions, and so on. The problem is denoted as LMDP-SODP, where SODP stands for Service Options and Drivers' Preferences. The main notations used to describe the problem are listed in Table 1.

2.2 Illustrative Example

The Figure 1 illustrates a feasible solution for LMDP-SODP. It shows the routes of three different vehicles,

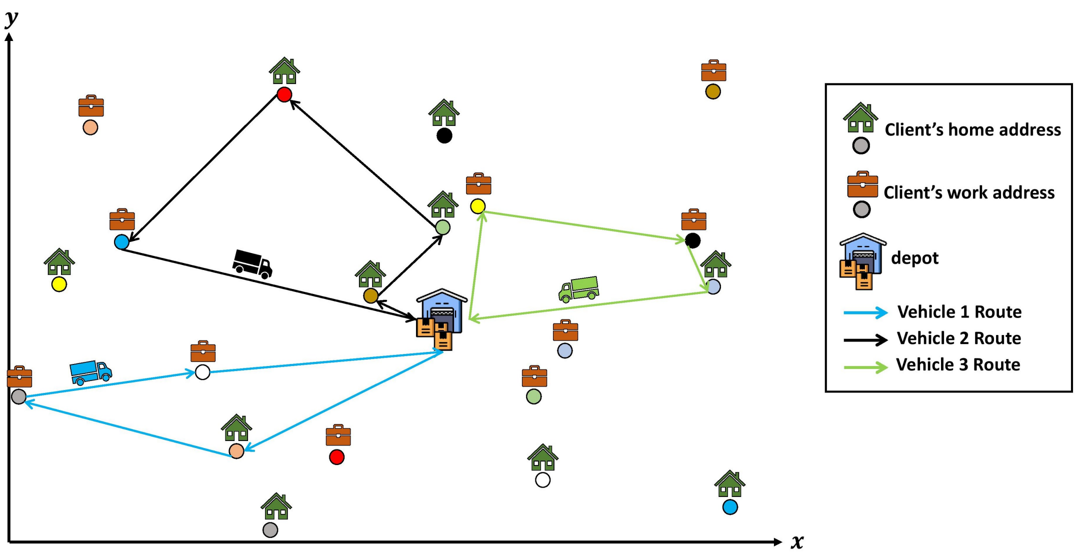

Figure 1: Illustration of a feasible solution to the LMDP-SODP with $n' = 10$ and $m = 3$.

each represented by a different color, starting from the depot and visiting 10 clients. Each client is depicted with two possible delivery locations: one for the home address and one for the work address, and the vehicles are assigned to visit one of these addresses based on the model optimization criteria. The figure visually demonstrates how each vehicle is routed to minimize total delivery cost by considering various factors, including drivers' distance-based preferences, familiarity with the area, traffic conditions, ease of access to delivery locations, and so on.

3 MATHEMATICAL FORMULATION

This section introduces a novel MIP formulation, tailored for addressing the LMDP-SODP. The problem can be formulated as a VRP that incorporates alternative locations and drivers' preferences.

The delivery route planner must decide on optimal routes for delivery vehicles that satisfy all constraints while minimizing total cost.

3.1 Objective Function

$$\min \sum_{k\in\mathcal{V}} \left(\sum_{i\in\Omega} \sum_{\substack{j\in\Omega\\ i\neq j}} \alpha_k \, d_{i,j} x_{i,j,k} + \sum_{i\in\Omega\setminus\{1\}} \beta_{k,i} y_{k,i} \right) \quad (1)$$

The objective function (1) aims to optimize the total operational cost. The operational cost is induced by the overall remuneration paid to the drivers. A driver's remuneration consists of two parts: The first part is based on the remuneration per traveled distance, while the second is based on the fee paid for each served customer.

3.2 Constraints

$$\sum_{j\in\Omega\setminus\{1\}} x_{1,j,k} = 1 \quad \forall k \in \mathcal{V} \quad (2)$$

$$\sum_{i\in\Omega\setminus\{1\}} x_{i,1,k} = 1 \quad \forall k \in \mathcal{V} \quad (3)$$

$$\sum_{\substack{i\in\Omega\\ i\neq j}} \sum_{k\in\mathcal{V}} x_{i,j,k} + \sum_{\substack{i\in\Omega\\ i\neq j+n-1}} \sum_{k\in\mathcal{V}} x_{i,j+n-1,k} = 1 \quad \forall j \in \mathcal{N} \quad (4)$$

$$\sum_{\substack{j\in\Omega\\ j\neq i}} \sum_{k\in\mathcal{V}} x_{i,j,k} + \sum_{\substack{j\in\Omega\\ j\neq i+n-1}} \sum_{k\in\mathcal{V}} x_{i+n-1,j,k} = 1 \quad \forall i \in \mathcal{N} \quad (5)$$

$$\sum_{\substack{i\in\Omega\\ i\neq l}} x_{i,l,k} = \sum_{\substack{j\in\Omega\\ j\neq l}} x_{l,j,k} \quad \forall l \in \Omega\setminus\{1\}, \forall k \in \mathcal{V} \quad (6)$$

$$y_{k,i} = \sum_{\substack{j\in\Omega\\ j\neq i}} x_{i,j,k} \quad \forall i \in \mathcal{N}, \forall k \in \mathcal{V} \quad (7)$$

$$u_i - u_j + (2n-m)\sum_{k\in\mathcal{V}} x_{i,j,k} \leq 2n-m-1 \, \forall i \neq j \in \Omega\setminus\{1\} \quad (8)$$

Constraints (2) and (3) ensure that each vehicle departs from and returns to the depot (node 1). Constraint set (4) ensures that each client is serviced by exactly one vehicle. Constraint set (5) ensures that each client's main or alternative address is serviced by exactly one vehicle, maintaining consistency in the delivery process. The flow conservation constraint (6) ensures that each vehicle's arrival at any node implies its departure from that node, maintaining the balance of vehicles in the network. Constraint (7) indicates whether a node is visited by a vehicle, aiding in route planning. The subtour elimination constraint (8) ensures the absence of subtours in the solution.

3.3 Domains

$$x_{i,j,k} \in \{0,1\} \quad \forall i,j \in \Omega, \forall k \in \mathcal{V} \tag{9}$$

$$y_{k,i} \in \{0,1\} \quad \forall k \in \mathcal{V}, \forall i \in \Omega \tag{10}$$

$$u_i \in \mathbb{N} \quad \forall i \in \Omega, \forall k \in \mathcal{V} \tag{11}$$

Constraints (9), (10) and (11) define the decision variables $x_{i,j,k}$ and $y_{k,i}$ as binaries, and u_i as positive integer variables, respectively, representing the travel and sequencing decisions of vehicles.

With the framework and methodology established, we now turn our attention to the computational results, which illustrate the effectiveness of our model in optimizing delivery routes and minimizing costs, all while accommodating drivers' preferences.

4 COMPUTATIONAL RESULTS

In this section, we conduct a performance analysis, over instances of different sizes, of the MIP formulation using the IBM ILOG CPLEX 22.1 solver with default settings. In the computational experiments, we used a personal computer equipped with an Intel(R) Core(TM) i7-7700HQ CPU operating at 2.8 GHz, accompanied by 8GB of RAM. The MIP formulation is analyzed based on the following metrics:

- The objective value of the test instances solved to optimality within 3600 s: *Opt*.
- The time required for solving these optimally solved instances: *CPU* (in seconds (sec)).
- The objective function value of the instances unsolved within 3600 s (instances with feasible solutions): *Best Integer*.
- The optimality gap for the test instances which could not be solved within 3600 s: *Gap(%)*.

4.1 Benchmark Instances

The characteristics of the generated test instances are summarized as follows:

- The coordinates (x_i, y_i) for each client i are generated randomly from a uniform distribution $U(0,100)$.
- The number of clients n' is selected from the set $\{10,20,25,30\}$, while the number of vehicles m is selected from $\{2,3,4\}$.

For each combination of values (n',m), a total of 10 distinct problem instances were generated, resulting in a total of 120 unique problem instances.

4.2 Real-World Data for Parameters

Inspired by real-world companies and their pricing schemes, the parameters α_k and $\beta_{k,i}$ are generated to reflect real-world scenarios.

Parameter α_k: The value of α_k is generated randomly within the range [0.5, 1.2] MAD (Moroccan Dirham) per kilometer, inspired by the pricing strategies of some companies in Morocco. These values are reflective of payments made to delivery drivers in real-world scenarios.

Parameter $\beta_{K,i}$: The value of $\beta_{k,i}$ accounts for both distance-based factors and drivers' preferences. While the distance $d_{k,i}$ between vehicle k and client i plays a central role in determining $\beta_{k,i}$, additional considerations such as drivers' familiarity with the neighborhood, traffic conditions, and ease of access to the delivery location are also integrated into the overall cost.

The cost rates for $\beta_{k,i}$ are inspired by real-world delivery pricing, where the minimum charge is 4 MAD and the maximum is 12 MAD. Specifically:

- When the distance $d_{k,i} = 0$ (i.e., the closest possible distance between vehicle k and client i), and other factors are most favorable (e.g., familiarity with the area, minimal traffic), $\beta_{k,i}$ is set to 4 MAD, representing the base cost.
- For the maximum distance $d_{k,i}^{\max}$ and less favorable conditions (e.g., unfamiliar areas, traffic congestion), $\beta_{k,i}$ is set to 12 MAD, representing the highest cost.

Thus, the parameter $\beta_{k,i}$ is generated using a uniform distribution $U(4,12)$, which captures the variability in delivery costs while maintaining a realistic representation of the delivery cost structure observed in practice. This approach ensures that the drivers' preferences and operational efficiencies are considered in route planning and assignment of delivery points. Additionally, the uniform distribution allows for a straightforward adjustment of the cost structure, making it easier to model different scenarios in the optimization process.

Table 2: Evaluation of MIP formulation for the LMDP-SODP with small instances ($n' \in \{10,20\}$).

Problem Instance			MIP				Problem Instance			MIP			
n'	m	Instance	Objective value: *Opt*	Objective value: *Best integer*	*Gap* (%)	*CPU* (sec)	n'	m	Instance	Objective value: *Opt*	Objective value: *Best integer*	*Gap* (%)	*CPU* (sec)
10	2	I01	**233.10**	—	0.00	1.46	20	2	I31	**318.51**	—	0.00	703.52
		I02	**256.81**	—	0.00	3.15			I32	**413.94**	—	0.00	161.23
		I03	**205.10**	—	0.00	1.31			I33	**337.38**	—	0.00	432.24
		I04	**302.12**	—	0.00	3.08			I34	**401.58**	—	0.00	151.84
		I05	**245.66**	—	0.00	1.82			I35	**366.02**	—	0.00	1126.10
		I06	**257.84**	—	0.00	1.39			I36	**426.65**	—	0.00	112.20
		I07	**297.92**	—	0.00	21.88			I37	**411.28**	—	0.00	172.89
		I08	**209.54**	—	0.00	1.26			I38	**332.36**	—	0.00	158.10
		I09	**245.28**	—	0.00	2.56			I39	**392.38**	—	0.00	147.27
		I10	**231.61**	—	0.00	1.57			I40	**365.00**	—	0.00	362.51
10	3	I11	**273.80**	—	0.00	1.51	20	3	I41	**366.27**	—	0.00	2.14
		I12	**330.01**	—	0.00	3.35			I42	**359.40**	—	0.00	18.27
		I13	**267.46**	—	0.00	1.56			I43	**389.16**	—	0.00	215.74
		I14	**298.25**	—	0.00	0.96			I44	**376.86**	—	0.00	105.12
		I15	**372.23**	—	0.00	0.84			I45	**441.09**	—	0.00	769.14
		I16	**234.89**	—	0.00	1.03			I46	**336.63**	—	0.00	1273.27
		I17	**261.39**	—	0.00	1.25			I47	**364.95**	—	0.00	22.62
		I18	**349.84**	—	0.00	0.90			I48	**350.73**	—	0.00	177.60
		I19	**328.50**	—	0.00	1.11			I49	**396.58**	—	0.00	915.56
		I20	**324.20**	—	0.00	0.81			I50	**357.24**	—	0.00	1808.93
10	4	I21	**375.51**	—	0.00	0.51	20	4	I51	**404.13**	—	0.00	30.65
		I22	**463.25**	—	0.00	1.21			I52	**400.03**	—	0.00	12.35
		I23	**383.95**	—	0.00	0.42			I53	**412.24**	—	0.00	52.80
		I24	**436.43**	—	0.00	0.49			I54	**404.74**	—	0.00	46.97
		I25	**321.37**	—	0.00	0.66			I55	**359.76**	—	0.00	41.21
		I26	**277.18**	—	0.00	0.41			I56	**519.44**	—	0.00	157.50
		I27	**428.94**	—	0.00	1.69			I57	**354.11**	—	0.00	13.51
		I28	**271.61**	—	0.00	1.46			I58	**498.71**	—	0.00	47.07
		I29	**462.79**	—	0.00	1.72			I59	**382.58**	—	0.00	100.31
		I30	**488.11**	—	0.00	0.44			I60	**326.83**	—	0.00	150.58

The computational results presented hereafter are structured to evaluate the effectiveness of the MIP formulation across varying instance sizes. Initially, we focus on small instances, followed by an analysis of the model's performance on medium-sized and large instances.

4.3 Evaluation of MIP for LMDP-SODP

This section presents the computational results for the benchmark instances of the LMDP-SODP, where we evaluate the performance of the developed MIP. The instances are defined by $n' \in \{10,20,25,30\}$ and $m \in \{2,3,4\}$, where n' represents the number of clients and m the number of vehicles. The instances can be classified into small ($n' \in \{10,20\}$) and medium/large ($n' \in \{25,30\}$) sets. For each value of the combination (n',m), 10 instances are generated, resulting in a total of 120 instances.

The results are comprehensively described and detailed in Table 2 for small instances and Table 3 for medium and large instances. The analysis of the results reveals several insights:

- For small instances ($n' \in \{10,20\}$) and ($m \in \{2,3,4\}$), the MIP consistently achieves optimal solutions within the time limit for all instances. This demonstrates the robustness and efficiency of the formulation in solving less complex scenarios.
- For medium instances ($n' = 25$) with $m = 2$, the MIP reaches optimality in 6 out of 10 instances, while in the remaining cases, a feasible solution (*Best Integer*) is found within the 3600-second time limit. Although not all instances are solved optimally, the model still provides high-quality solutions.
- When $n' = 25$ and $m = 3$, the model attains optimal solutions in 4 out of 10 instances. Similar to the previous case, a feasible solution is obtained for the remaining instances within the time constraint, underscoring the gradual increase in complexity as m grows.
- For $n' = 25$ and $m = 4$, the MIP model successfully reaches optimality in 7 out of 10 instances. For the remaining cases, a feasible solution (*Best Integer*) is still computed within the allotted time, confirming the model's capacity to handle higher complexity to some extent.
- For the larger instances where $n' = 30$ and $m \in \{2,3\}$, the MIP finds optimal solutions for only 1 out of 10 instances. Despite the difficulty in achieving optimality, feasible solutions are ob-

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Table 3: Evaluation of MIP formulation for the LMDP-SODP with medium and large instances ($n' \in \{25, 30\}$).

Problem Instance			MIP				Problem Instance			MIP			
n'	m	Instance	Objective value		*Gap* (%)	*CPU* (sec)	n'	m	Instance	Objective value		*Gap* (%)	*CPU* (sec)
			Opt	*Best integer*						*Opt*	*Best integer*		
25	2	I61	**410.77**	—	0.00	722.71	30	2	I91		473.05	11.94	3600
		I62	**475.63**	—	0.00	1097.87			I92	**393.13**	—	0.00	327.95
		I63		556.69	4.14	3600			I93		456.47	9.46	3600
		I64	**359.64**	—	0.00	251.74			I94		554.65	9.91	3600
		I65		390.72	5.67	3600			I95		520.57	16.96	3600
		I66		379.10	1.36	3600			I96		501.70	3.50	3600
		I67	**373.79**	—	0.00	47.40			I97		403.42	2.16	3600
		I68	**465.86**	—	0.00	148.90			I98		375.77	5.31	3600
		I69	**470.58**	—	0.00	191.54			I99		405.62	4.37	3600
		I70		378.63	5.96	3600			I100		502.25	5.36	3600
25	3	I71		471.57	7.15	3600	30	3	I101		392.42	4.37	3600
		I72	**433.68**	—	0.00	48.10			I102		505.97	6.78	3600
		I73	**442.66**	—	0.00	277.05			I103		559.56	2.39	3600
		I74	**536.17**	—	0.00	60.64			I104		473.76	3.29	3600
		I75		398.18	7.45	3600			I105		495.75	10.11	3600
		I76		401.56	5.03	3600			I106		568.01	5.71	3600
		I77		477.24	6.44	3600			I107		625.09	8.10	3600
		I78	**399.39**	—	0.00	40.84			I108		436.01	6.77	3600
		I79		398.37	2.45	3600			I109	**441.01**	-	0.00	787.25
		I80		388.74	6.44	3600			I110		499.56	12.41	3600
25	4	I81	**482.60**	—	0.00	233.42	30	4	I111		557.62	5.50	3600
		I82	**378.77**	—	0.00	222.28			I112		463.12	2.85	3600
		I83		486.58	2.51	3600			I113		546.66	11.21	3600
		I84	**426.21**	—	0.00	1463.68			I114	**521.10**	—	0.00	687.66
		I85	**585.36**	—	0.00	743.51			I115		457.46	9.57	3600
		I86	**390.97**	—	0.00	511.96			I116	**562.44**	—	0.00	525.87
		I87	**470.73**	—	0.00	544.58			I117		538.89	4.34	3600
		I88		447.26	1.12	3600			I118		475.30	3.67	3600
		I89		459.45	3.67	3600			I119		512.53	10.81	3600
		I90	**523.83**	—	0.00	441.01			I120		504.36	4.48	3600

tained for the other instances within the time limit, suggesting that these cases are considerably more challenging.

- In the case where $n' = 30$ and $m = 4$, the model solves 2 out of 10 instances to optimality, with feasible solutions (*Best Integer*) provided for the remaining instances within the 3600-second time frame. This further highlights the increased difficulty when both n' and m reach their maximum values in this benchmark.

These results indicate that while the MIP formulation performs well across different problem configurations, there is a slight decrease in performance as the problem size and complexity increase. Nonetheless, the model exhibits resilience by consistently finding solutions, either optimal or near-optimal, within the allotted time frame.

5 CONCLUSIONS

In this study, conducted as part of a research project on logistics and urban mobility, we addressed the Last Mile Delivery Problem with consideration for both Service Options and Drivers' Preferences (LMDP-SODP). The objective function aimed to optimize delivery routes to minimize the total distance traveled by vehicles, whether they are company employees or crowd-shippers called upon depending on the workload, while taking into account their preferences. To achieve this, we developed a novel Mixed Integer Programming (MIP) formulation to optimally solve the problem. To evaluate the performance of our proposed mathematical formulation, we conducted extensive computational experiments using generated benchmark instances. In terms of computational efficiency, the MIP model was capable of solving all instances with up to 20 clients (i.e., 40 locations) and 4 delivery vehicles. For instances with 25 and 30 clients, using 2 to 4 vehicles, optimal or feasible solutions were obtained in the best cases. Furthermore, the use of crowd-shippers with clean modes of transport, delivering to regions they are most familiar with, can have a positive impact on cost reduction, environmental sustainability, and customer satisfaction.

Potential future research directions could involve several aspects. LMD can be improved by leveraging Artificial Intelligence techniques, such as machine learning algorithms, reinforcement learning, and neural networks, to enhance optimization and decision-making processes. Using eco-friendly transport and non-professional drivers can make deliveries more sustainable and satisfy customers. The model can also

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include multiple alternative addresses, each with different time windows and costs. Additionally, delving into the integration of advanced optimization techniques, such as heuristics or metaheuristics, could effectively handle large-scale problems. Efficient logistics systems are important for dealing with urban challenges and meeting growing delivery demands.

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REFERENCES

Al Hla, Y. A., Othman, M., and Saleh, Y. (2019). Optimising an eco-friendly vehicle routing problem model using regular and occasional drivers integrated with driver behaviour control. *Journal of Cleaner Production*, 234:984–1001.

Amaral, J. C. and Cunha, C. B. (2020). An exploratory evaluation of urban street networks for last mile distribution. *Cities*, 107:102916.

Anily, S. (1996). The vehicle-routing problem with delivery and back-haul options. *Naval Research Logistics (NRL)*, 43(3):415–434.

Archetti, C., Savelsbergh, M., and Speranza, M. G. (2016). The vehicle routing problem with occasional drivers. *European Journal of Operational Research*, 254(2):472–480.

Benmansour, R., Darvish, M., Todosijević, R., and Zufferey, N. (2024). Variable neighbourhood search for parallel machine scheduling with a single loading server: a truck-scheduling perspective. In *Supply Chain Forum: An International Journal*, pages 1–13. Taylor & Francis.

Cardeneo, A. (2005). *Modellierung und Optimierung des B2C-Tourenplanungsproblems mit alternativen Lieferorten und-zeiten*. KIT Scientific Publishing.

Cordeau, J.-F., Gendreau, M., Laporte, G., Potvin, J.-Y., and Semet, F. (2002). A guide to vehicle routing heuristics. *Journal of the Operational Research society*, 53(5):512–522.

Dragomir, A. G., Van Woensel, T., and Doerner, K. F. (2022). The pickup and delivery problem with alternative locations and overlapping time windows. *Computers & Operations Research*, 143:105758.

Eksioglu, B., Vural, A. V., and Reisman, A. (2009). The vehicle routing problem: A taxonomic review. *Computers & Industrial Engineering*, 57(4):1472–1483.

Golden, B. L., Raghavan, S., and Wasil, E. A. (2008). *The vehicle routing problem: latest advances and new challenges*, volume 43. Springer Science & Business Media.

Jazemi, R., Alidadiani, E., Ahn, K., and Jang, J. (2023). A review of literature on vehicle routing problems of last-mile delivery in urban areas. *Applied Sciences*, 13(24):13015.

Kiba-Janiak, M., Marcinkowski, J., Jagoda, A., and Skowrońska, A. (2021). Sustainable last mile delivery on e-commerce market in cities from the perspective of various stakeholders. literature review. *Sustainable Cities and Society*, 71:102984.

Laporte, G. (2009). Fifty years of vehicle routing. *Transportation science*, 43(4):408–416.

Los, J., Spaan, M. T., and Negenborn, R. R. (2018). Fleet management for pickup and delivery problems with multiple locations and preferences. In *Dynamics in Logistics: Proceedings of the 6th International Conference LDIC 2018, Bremen, Germany*, pages 86–94. Springer.

Macrina, G., Di Puglia Pugliese, L., Guerriero, F., and Laganà, D. (2017). The vehicle routing problem with occasional drivers and time windows. In *Optimization and Decision Science: Methodologies and Applications: ODS, Sorrento, Italy, September 4-7, 2017 47*, pages 577–587. Springer.

Pahwa, A. and Jaller, M. (2022). A cost-based comparative analysis of different last-mile strategies for e-commerce delivery. *Transportation Research Part E: Logistics and Transportation Review*, 164:102783.

Pourmohammadreza, N. and Jokar, M. R. A. (2023). A novel two-phase approach for optimization of the last-mile delivery problem with service options. *Sustainability*, 15(10):8098.

Prodhon, C. and Prins, C. (2014). A survey of recent research on location-routing problems. *European journal of operational research*, 238(1):1–17.

Strulak-Wójcikiewicz, R. and Wagner, N. (2021). Exploring opportunities of using the sharing economy in sustainable urban freight transport. *Sustainable Cities and Society*, 68:102778.

Tilk, C., Olkis, K., and Irnich, S. (2021). The last-mile vehicle routing problem with delivery options. *Or Spectrum*, 43(4):877–904.

Todosijević, R., Hanafi, S., Urošević, D., Jarboui, B., and Gendron, B. (2017). A general variable neighborhood search for the swap-body vehicle routing problem. *Computers & Operations Research*, 78:468–479.

Torres, F., Gendreau, M., and Rei, W. (2022a). Crowdshipping: An open vrp variant with stochastic destinations. *Transportation Research Part C: Emerging Technologies*, 140:103677.

Torres, F., Gendreau, M., and Rei, W. (2022b). Vehicle routing with stochastic supply of crowd vehicles and time windows. *Transportation Science*, 56(3):631–653.

Toth, P. and Vigo, D. (2002). *The vehicle routing problem*. SIAM.

Toth, P. and Vigo, D. (2014). *Vehicle routing: problems, methods, and applications*. SIAM.

United Nations, Department of Economic and Social Affairs, Population Division (2022). World Population Prospects 2022: Summary of Results. UN DESA/POP/2022/TR/NO. 3.

Vidal, T., Laporte, G., and Matl, P. (2020). A concise guide to existing and emerging vehicle routing problem variants. *European Journal of Operational Research*, 286(2):401–416.

Von Boventer, E. (1961). The relationship between transportation costs and location rent in transportation problems. *Journal of Regional Science*, 3(2):27–40.

Watson-Gandy, C. and Dohrn, P. (1973). Depot location with van salesmen—a practical approach. *Omega*, 1(3):321–329.

Webb, M. (1968). Cost functions in the location of depots for multiple-delivery journeys. *Journal of the Operational Research Society*, 19(3):311–320.

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