International Journal of Industrial Engineering Computations 15 (2024) 367–386

Contents lists available at GrowingScience

International Journal of Industrial Engineering Computations

homepage: www.GrowingScience.com/ijiec

Efficient last-mile logistics with service options: A multi-criteria decision-making and optimization methodology

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C H R O N I C L E

Article history:
Received October 27 2023
Received in Revised Format January 29 2024
Accepted February 19 2024
Available online February 19 2024

Keywords:
Vehicle Routing Problem
Last-mile logistics
Service Options
Normalized Normal Constraint
Mathematical Programming
Multi-Criteria Decision-Making

A B S T R A C T

The rapid growth of online shopping has intensified the need for cost-effective and efficient delivery systems, posing a significant challenge for businesses worldwide. This study proposes an innovative two-phase methodology that uses a hybrid multi-criteria decision-making (MCDM) approach for efficient last-mile logistics with service options (ELMLSO) such as home delivery, self-pickup, and differently-priced services. This approach aims to streamline last-mile logistics by integrating these service options, resulting in a more comprehensive and effective delivery network that enhances customer satisfaction and maintains a competitive edge. The first phase employs the Ordinal Preference Analysis - Evaluation based on Distance from Average Solution (OPA-EDAS) method to select optimal pickup and delivery centers. The second phase identifies the optimal route using a bi-objective mixed-integer mathematical model, striving to balance cost minimization and customer satisfaction maximization. The Normalized Normal Constraint Method (NNCM) is utilized to solve this model. The application of these methods results in considerable cost savings and improved customer satisfaction, offering valuable insights for managers within the last-mile logistics industry.

1. Introduction

Last-mile logistics (LML) represents the final segment in the business-to-consumer (B2C) parcel delivery process. This phase involves the journey of the parcel from the order fulfillment center to the chosen destination of the end recipient (Lim et al., 2018). The LML is widely seen as the most essential and complex part of the delivery process, involving significant logistical challenges, and directly impacting the effectiveness and efficiency of the entire distribution system, as it can be expensive, time-consuming, and subject to a range of logistical challenges, such as traffic limited access to delivery locations (Boysen et al., 2021; Ranieri et al., 2018).

The LML is also an essential component of the supply chain that plays a crucial role in ensuring customer satisfaction (Lai et al., 2022) , delivery speed and reliability (Halldórsson & Wehner, 2020), cost efficiency (Cortes & Suzuki, 2022), urbanization trends (Cardenas et al., 2017), and environmental sustainability (Melkonyan et al., 2020). In today's world, customers expect fast and reliable delivery, and the last-mile is the point where the customer interacts with the delivery provider (Chen & Pan, 2016). Therefore, a positive LML experience is critical to meeting customer expectations and ensure satisfaction.

The importance of the last stage is underscored by its significant contribution to the overall cost, reportedly up to 50% (Company, 2016), and its impact on the customer experience. A study by Capgemini revealed that 97% of customers consider the last-mile the most important part of their delivery experience, with 55% willing to switch retailers following a poor LML experience (Capgemini, 2017). Moreover, the LML market is expected to reach $65.2 billion by 2025 (Research and Markets, 2020). These statistics underscore the importance of efficient last-mile delivery, further amplified by the COVID-19 pandemic's surge in e-commerce sales and the demand for delivery services (Digital Commerce 360, 2020).

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ISSN 1923-2934 (Online) - ISSN 1923-2926 (Print)
2024 Growing Science Ltd.
doi: 10.5267/j.ijiec.2024.2.003

Optimizing LML can help reduce costs and increase profitability for businesses (Ranieri et al., 2018). Strategies such as route optimization, alternative delivery methods, and consolidation can help businesses improve their delivery efficiency and reduce the cost of goods delivery (Christopher, 1999). With more people living in urban areas, LML has become even more critical. Urbanization has made it more challenging and costly to make deliveries, but it is also where the demand for fast and efficient delivery is highest (Allen et al., 2018). Therefore, businesses that can optimize LML in urban areas can gain a competitive advantage.

Moreover, LML can have a significant environmental impact due to emissions from delivery vehicles and the use of packaging materials (Niemeijer & Buijs, 2023; Yavari et al., 2022). Therefore, finding ways to make LML more sustainable is critical to reducing the environmental impact of the delivery process. Strategies such as alternative delivery methods, route optimization, and sustainable packaging assist companies in lowering their carbon emissions, thereby supporting environmental sustainability.

Efficient last-mile logistics (ELML), refers to the use of optimized routing and scheduling algorithms, and other strategies to reduce the cost, time, and environmental impact of LML (Dell'Amico & Hadjidimitriou, 2012). This can include the use of parcel lockers, pickup points, drones, and autonomous vehicles, as well as advanced analytics and decision-making to optimize routes and delivery schedules.

The necessity of moving toward ELML is driven by several factors, including:

The rapid growth of e-commerce: With the explosive growth of online shopping, the need for LML services has skyrocketed. In order to meet this demand, companies must find ways to deliver goods more efficiently and cost-effectively.

Environmental concerns: LML is a major contributor to traffic congestion, air pollution, and carbon emissions. By moving toward more efficient LML methods, companies can reduce their environmental impact and contribute to a more sustainable future.

Customer expectations: Customers today expect fast, reliable, and convenient delivery options. By improving the efficiency of LML, companies can meet these expectations and provide a better overall customer experience.

In LML, the primary form of service rendered is home delivery (HD), which involves a team of couriers delivering parcels to customers' homes or places of employment (Seghezzi et al., 2022). In addition to home delivery, two new points for delivery are emerging in LML: parcel lockers and pickup points (PPs). Parcel lockers are secure storage units located in public places, while PPs are designated locations where customers can collect their packages (Lee et al., 2020). Both options offer increased flexibility, reduced delivery times, and improved efficiency for delivery companies. These new points for delivery are helping to meet the growing demand for fast and reliable delivery services and are improving the overall LML experience for both customers and logistics companies.

VRP models can help improve efficient LML (Yang et al., 2020; Zhou et al., 2018). VRP models are mathematical optimization models used to solve routing problems, including LML (Berahhou et al., 2022). By considering numerous elements such as delivery location, vehicle capacity, and delivery time windows. VRP models assist delivery businesses in enhancing their delivery routes and efficiency, leading to cost reductions and more effective deliveries (Ancele et al., 2021; Jiang et al., 2024). Advanced VRP models can help delivery companies improve the overall efficiency of LML by ensuring their deliveries are timely and cost-effective (Moghaddam et al., 2012).

The presented approach in this paper to ELML involves two phases:

1. Multi-Attribute Decision-Making (MADM) Approach: The first phase of our approach involves using a MADM method to determine the proper pickup and delivery centers (PDCs) for delivery operations. MADM methods help decision-makers evaluate and compare multiple criteria simultaneously, taking into account factors such as distance, cost, accessibility, and service quality. By using a MADM approach, we can ensure that we select the best PDC based on a range of factors, rather than relying on a single criterion.

2. VRPSO: The second phase of the approach involves using a VRP model with service options (SO) and pickup and delivery (PD) and time windows (TW) constraints to optimize the delivery routes to minimize travel time, distance, and cost and maximize improve customer satisfaction.

Overall, we aim to maximize the efficiency of LML operations by implementing novel a two-phase strategy. First, we utilize a hybrid Multi-Attribute Decision Making (MADM) approach to select the optimal PDCs. Second, we employ a VRPSO model with PD and TWs (VRPSOTWPD) to optimize our delivery routes and improve customer satisfaction.

The contributions of this paper are fourfold:

- ✓ Presentation of an innovative variation of the VRP, by proposing VRPSOs encompassing PD with TW, taking into account HD, self-pickup, and various pricing options for delivery services.
- ✓ This paper introduces a customer-empowering approach for selecting service options based on preferences, and provides an analysis of the resulting customer satisfaction levels.

- ✓ The proposition of a cutting-edge strategic and operational methodology in VRP challenges. A MADM model, OPA-EDAS, is introduced for evaluating and selecting PDCs, followed by the formulation of a customized bi-objective mixed-integer linear program in the subsequent phase.
- ✓ Offering a holistic solution to the efficient LML problem, considering both cost-effectiveness and customer satisfaction objectives.

The structure of this study is as follows: Section 2 presents an overview of the literature. In Section 3, first, we determine the key factors that are essential for selecting the appropriate PDCs. Then, we use an OPA-EDAS method to rank the available options and select the most appropriate PDCs based on various criteria. We then define the problem statement, underlying assumptions, and parameters of the proposed VRPSO model. Section 4 presents a case study to solve and evaluate the proposed approach. In Section 5, a sensitivity analysis is performed to assess the robustness of the proposed LML model. Section 6 provides the managerial insights derived from the study. Lastly, Section 7 summarizes the significant findings and proposes directions for future research.

2. Literature Review:

2.1 VRP with Delivery Options or Roaming Delivery Locations

The recent shift towards online shopping has increased the demand for varied delivery options and led to the evolution of specialized VRP variants. Two notable ones are VRP with Delivery Options (VRPDOs) and VRP with Roaming Delivery Locations (VRPRDL), each addressing unique challenges in LML. Savelsbergh and Van Woensel (2016) threw light upon the contemporary and future challenges and prospects related to urban logistics, with a spotlight on the indispensable function of pickup-point systems in forging steadfast LML networks.

Reyes and colleagues blazed a trail in tackling the conundrum of parcel delivery to roaming customer locations. They laid the groundwork for VRPRDL and brought to the table an innovative algorithm built on dynamic programming (Reyes et al., 2017). In VRPRDL, the target is to pinpoint the supreme route for vehicles delivering items to a car without being constrained by its stationary location, anchored by the customer's established travel route. This problem was cast as a set-covering quandary and tackled through a branch-and-price algorithm (Ozbaygin et al., 2017; Reyes et al., 2017). These manuscripts stand as the vanguard in the VRPRDL arena.

A subsequent wave of research considered realistic scenarios, such as (Lombard et al., 2018; Sampaio et al., 2019), which explored VRPRDL in the context of stochastic travel times. In VRPRLD, there is a sharing of customer-related information like traffic updates, whereas in VRPDOs, customers wield the choice of location. HD and Self-Delivery Locations (SDL) were probed in tandem by Zhang and Lee, (2016). The model focuses on identifying delivery routes and destinations that meet specific requirements and goals, once customers earmark their preferred delivery locations. He et al. gave thought to dynamic customers with dual services, incorporating waiting time into the objective function (He et al., 2019). Mancini and Gansterer broached VRP with private and shared delivery locations, thereby offering customers the latitude to opt for home service or self-pickup from a depot, underlining that offering more options paves the way for cost-efficient routes (Mancini & Gansterer, 2021).

In yet another intriguing development, Grabenschweiger *et al.* (2021) scrutinized the VRP with a focus on diverse locker boxes. They formulated a mathematical model that aimed at minimizing the cumulative cost, encapsulating both routing and compensation costs, and streamlining the packing of parcels into lockers. A metaheuristic methodology was advocated to trim the aggregate costs. In a novel approach, Schwerdfeger and Boysen, (2020) gave thought to the utilization of mobile locker boxes, which possess the adaptability to modify their location in real-time. They posited that fine-tuning the locker boxes' location could bolster accessibility for consumers. The problem they addressed involved reducing the number of locker boxes while ensuring comprehensive customer satisfaction.

In summary, the spurt in online shopping has catalyzed the emergence of advanced models in last-mile logistics, notably VRPOD, and VRPRLD, addressing the dynamic nature of delivery locations and services. Research in this domain has gradually evolved to incorporate real-world complexities and constraints, optimizing routes while considering customer preferences, vehicle capacities, and TWs. The integration of modern technologies, like locker boxes and information sharing, further enhances the efficiency and cost-effectiveness of LML systems.

2.2 MADM methods for optimizing last-mile logistics efficiency

MADM methods involve the use of mathematical models that consider the preferences of decision-makers in evaluating alternative solutions. These preferences can be expressed using a variety of techniques, such as pairwise comparison, rating, or ranking. Once the preferences are obtained, the MADM model evaluates each alternative solution based on its performance with respect to each objective and produces a ranking or selection of the best solution(s). Various studies have employed MADM techniques to address LML challenges, including the study by (Ferrer et al., 2018), which developed a model focused on multi-criteria optimization in the context of last-mile distribution for humanitarian aid. The model takes into account an array of performance criteria encompassing aspects like time, cost, coverage, equity, and security. Similarly, (Kwak & Kim,

2018) used AHP to determine the optimal logistics delivery method for B2C cross-border e-commerce, considering four options: EMS, international express, air transportation, and overseas warehouse, and found that overseas warehouse is the best option according to delivery price, delivery safety, and delivery price segmentation criteria. In spite of the variety and quantity of Pickup Point Problems (PPPs) studies, very few effectively inform decision-makers on how to select a PP. A limited number of studies have been conducted on PPPs. To choose models that will be most applicable to this setting, this work identifies the factors influencing pickup points' positioning, followed by optimizing the VRP and reducing travel expenses.

2.3 Multi-objective models for optimizing last-mile logistics efficiency

Multi-objective optimization models have been proposed to solve the LML problem with conflicting objectives, such as minimizing travel distance and maximizing customer satisfaction. Heng *et al*. proposed a new optimization model for efficiently routing different types of vehicles in urban LML with time-windows and pickup and delivery constraints while minimizing transportation costs and distances traveled (Heng et al., 2015). The model is solved using a modified NSGA-II algorithm considering multiple objectives, including vehicle load and capacity utilization. In another study Eydi and Ghasemi-Nezhad proposed a multi-objective optimization methodology aimed at tackling the timely delivery of products and curtailing travel expenses through the minimization of travel costs and maximization of customer demand fulfillment (Eydi & Ghasemi-Nezhad, 2021). Similarly, Melián-Batista *et al.* presented a bi-objective mixed-integer linear model for minimizing the total traveled distance while balancing drivers' workload in daily routes of a vehicle fleet, which is solved by a scatter search metaheuristic approach (Melián-Batista et al., 2014). The compilation of knowledge to date suggests that no extensive investigation into the diverse elements of LML has yet been completed. Table 1 provides a synopsis of the current research on VRP with Delivery Options and Self-Pickup. According to the data presented in Table 1, in the objective section, the 'C' represents objectives pertaining to costs or travel distances. 'CP' signifies the objective related to customer preferences, while 'O' stands for any other objectives that might not fit into the prior categories.

Table 1
Comparative analysis of research approaches and methodologies in last-mile logistics with delivery options

Article	DO[1]	Self-pickup	PD	TW	Priority[2]	Location Selection	Price	Objective			Solution
								C	CP	O	
(Zhang & Lee, 2016)		✓		✓				✓			Ant Colony Optimization
(Zhou et al., 2016)	✓	✓				✓		✓			Hunger Games Search (HGS)
(Ozbaygin et al., 2017)	✓			✓				✓			Branch and Price
(Reyes et al., 2017)	✓			✓				✓			Heuristics Based on Greedy Randomized Adaptive Search Procedures
(Los et al., 2018)	✓		✓		✓			✓	✓		Adaptive Large Neighborhood Search (ALNS)
(Zhou et al., 2018)	✓	✓	✓			✓		✓			HGS
(He et al., 2019)	✓			✓				✓			Large Neighborhood Search (LNS)
(Orenstein et al., 2019)		✓				✓		✓			Savings, Petal, Tabu Search, LNS
(Sampaio et al., 2019)	✓			✓				✓			Scenario-Based Stochastic Approximation
(Sitek & Wikarek, 2019; Sitek et al., 2021)	✓	✓	✓			✓	✓	✓			Variable Fixing
(Enthoven et al., 2020)		✓				✓		✓			ALNS
(He et al., 2020)	✓			✓	✓			✓		✓	Sample Average Approximation
(Dumez et al., 2021)	✓	✓		✓	✓	✓		✓			LNS
(Grabenschweiger et al., 2021)		✓		✓		✓	✓	✓			ALNS-bin-packing
(Mancini & Gansterer, 2021)		✓		✓		✓	✓	✓			Iterated Local Search (ILS), metaheuristic
(Tilk et al., 2021)	✓	✓		✓	✓	✓		✓			Branch-Price-and-Cut
(Yu et al., 2022)	✓	✓	✓	✓				✓			Simulated annealing
(Wang et al., 2022)	✓			✓		✓		✓			Robust Optimization
(Buzzega & Novellani, 2022)		✓		✓				✓			Branch and Cut
(Dragomir et al., 2022)	✓		✓	✓						✓	Multi-Start, Adaptive, Large Neighborhood Search (MSALNS)
(Friedrich & Elbert, 2022)	✓			✓		✓	✓	✓			ALNS
(Janinhoff et al., 2022)	✓	✓			✓	✓	✓	✓			ALNS
(Pourmohammadreza & Jokar, 2023)	✓	✓	✓		✓	✓	✓	✓			Branch and Cut
(Wang et al., 2023)		✓		✓		✓		✓			data-driven column generation algorithm and the rolling horizon approach (DCG)
This paper	✓	✓	✓	✓	✓	✓	✓	✓	✓		NNC; New hybrid MCDM method (OPA-EDAS)

[1] Delivery option
[2] Customer preferences

2.4 Literature Summary: Highlighting Gaps and Comparing with Current Research

Based on our analysis of current research, we have found that LML is becoming increasingly important due to the growing e-commerce industry and the desire for on-demand services. The efficiency of LML has evolved into a pivotal component for customer contentment, loyalty, and the overall success and efficiency of the transportation system. Here, we compare and contrast this research with the preceding scholarly works.

- Numerous studies in the literature have put forth a variety of VRP variants to provide effective solutions to improve the efficiency of LML. However, some of them either overlook service options such as home delivery, self-pickup, and delivery choices or contemplate them in isolation. In contrast, the current research introduces a novel variant, the VRPSO, that examines these options and offers a novel perspective on the problem.
- Our research uniquely equips customers with the ability to select from various service options based on their priorities and associated costs. We also contribute by introducing the consideration of TWs and PDCs at the same time in the VRPSO. By considering these factors together, we aim to provide a more efficient and effective solution that can improve the overall performance of LML.
- The paper brings forth a ground-breaking multi-criteria decision-making model (OPA-EDAS) capable of rating and selecting PDCs. A custom bi-objective mixed-integer linear programming model is also formulated to blend cost and customer satisfaction objectives effectively.
- The methodology adopted in our research considers the challenges of LML by balancing cost and customer satisfaction objectives. The NNCM further enhances the efficacy of the bi-objective VRPSO model, thereby ensuring dependable, efficient last-mile logistics.
- Both strategic and operational decisions in logistics are considered, with the overall transportation system being optimized through the strategic selection of PDCs and the addressing of operational routing solutions.

3. Methodology

This study addresses LMLSO, in which customers can choose home delivery, self-pickup, or a combination of both, with specific TWs for each service request. The objective is to develop an integrated framework for efficient last-mile Logistics planning (LMLP) while considering the operational and economic aspects and objectives of all stakeholders involved in the MADM and mathematical modeling. The proposed framework comprises two phases. In the first phase, relevant research and consultations with experts were employed to extract criteria for marketplace businesses, which were then weighted and scored using MCDM techniques, specifically the Ordinal Preference Analysis (OPA) and the Evaluation based on Distance from Average Solution (EDAS) methods. The second phase involves a bi-objective mixed integer mathematical model for VRPSO, which optimizes the routes for delivery and selects the best delivery option for each customer. Afterward, the bi-objective model from the second phase is solved using the NNC and branch and cut method. The proposed framework provides a comprehensive and efficient methodology for LMLP, taking into account customer preferences and multiple stakeholder objectives. The study proposes an integrated two-phase methodology (Fig. 1) for ELML that considers both customer satisfaction and profitability.

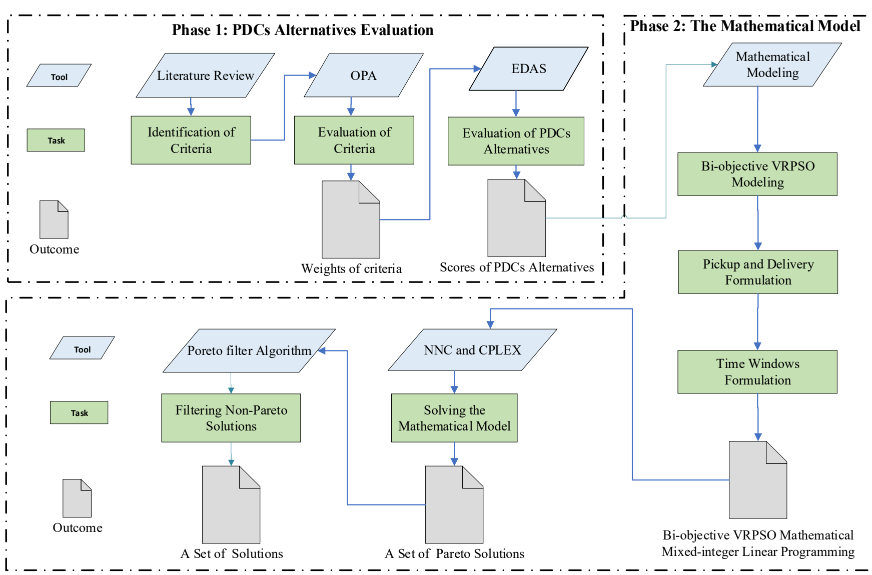

Fig. 1. Structure of the proposed approach

3.1 Phase1: OPA_EDAS method for assessing the pick-up points scores

In order to evaluate the PDCs, we first identify factors that affect them. Then, the structure of criteria is defined according to relations recognized among the PDCs. Then, the OPA is used to calculate the factor scores.

Step I: In response to the challenges posited in this research, a thorough and methodical review of existing papers, along with expert insights, was initially conducted. The investigation identified nine crucial criteria pivotal to the selection of PDCs within the framework of LML.

The factors are presented in Table 2, along with the explanations and sources for each one.

Table 2
Description of the key factors used to choose pick up points

Factor	Index	Description	sources
Availability	F_1	Possibility of parcel delivery 24/7	(Zenezini et al., 2018)(Lemke et al., 2016)(Tang et al., 2021)
Accessibility	F_2	Degree of connectivity with various facilities and transportation modes	(Stašys et al., 2022)(Tedjo et al., 2022)(Lemke et al., 2016)(Tang et al., 2021)
Security	F_3	The condition of not being in danger or threat	(B. Yu & Du, 2013)(Iwan et al., 2016)
Environmental Impact	F_4	Emissions from PPs and their effects on the environment	(Iwan et al., 2016)(Faugere & Montreuil, 2017)
Number of facility staff	F_5	Employees required in the facility	(Stašys et al., 2022)(Zenezini et al., 2018)
Costs	F_6	Estimate the price of the installation and maintenance of the parcel lockers.	(Zenezini et al., 2018)(Tedjo et al., 2022)(Lemke et al., 2016)
Methods of use	F_7	Procedures to implement to use the PPs	(Le et al., 2020)(Stašys et al., 2022)(Lemke et al., 2016)
Regulations	F_8	Official rules issued from different nations in order to regulate pick-up point activity.	(Lemke et al., 2016)(Lagorio & Pinto, 2020)
Capacity	F_9	Limitation on parcel number	(Lagorio & Pinto, 2020)(Zenezini et al., 2018)

Step II: After identifying the factors for selecting PDCs, we will employ the OPA approach. The OPA approach is a MADM technique that involves ranking alternatives based on the decision-makers' preference information (Ataei et al., 2020). This approach is particularly well-suited for our study, as it enables us to consider a range of different factors and to score the factors for use in selecting potential PDC locations.

OPA has some advantages over other decision-making methods in our problem, including its ability to handle both quantitative and qualitative criteria, its ease of use, and its ability to incorporate stakeholder preferences into the decision-making process. Moreover, it is a flexible method that can be adapted to a wide range of LML scenarios (Ataei et al., 2020).

By using the OPA approach, we can take into account the complex and interrelated nature of the criteria and ensure that our selection process is both rigorous and transparent. This will enable us to identify PDCs that are not only efficient and cost-effective, but also meet the diverse needs and preferences of customers and stakeholders. Incorporating OPA into our two-phase methodology for ELMLSO ensures that the resulting plans are not only optimal from an operational standpoint but are also grounded in the real-world preferences and priorities of the stakeholders involved.

Table 3 provides a comprehensive comparison between the OPA method and other frequently used MCDM methods. One of the most notable benefits of the OPA method, when compared to other methods, is its capacity to optimize outcomes using mathematical models. Moreover, OPA allows experts to evaluate only critical criteria and determine criteria weights alone, which is not possible with some other methods.

Table 3
Comparison between the OPA method and other frequently used MCDM methods

MCDM Method	AHP	DEMATEL	TOPSIS	COPRAS	Critic	SWARA	BWM	OPA
First Introduced	1972	1976	1981	1994	1994	2010	2015	2020
Necessity for Pairwise Comparison	Yes	Yes	No	No	Yes	No	Yes	No
Decision Matrix	No	No	Yes	Yes	Yes	Yes	No	No
Requirement for Normalization	No	No	Yes	Yes	Yes	Yes	No	No
Experts' Opinion Aggregation	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Only Critical Criteria Evaluation by Experts	No	No	No	No	No	No	No	Yes
Differentiation Between Benefit and Non-benefit Factors	No	No	Yes	Yes	No	No	No	No
Optimization of Results by Mathematical Model	No	No	No	No	No	No	Yes	Yes
The ability for Criteria Weight Determination	Yes	Yes	No	No	Yes	Yes	Yes	Yes

Step III: In the third step, the EDAS technique is utilized to rank and score pick-up locations, according to the criteria delineated in the preceding steps (Keshavarz Ghorabaee et al., 2015). EDAS, a comparatively novel approach within the realm of MCDM, considers the deviation of each choice from the mean solution.

We aimed to select the most appropriate PDC type for ELML. To achieve this, we started by introducing the factors that have a significant impact on our decision-making process. We then utilized the OPA method to score these factors based on their relative importance. After obtaining the scores, we employed the EDAS to sort the available options based on the factors scores. The findings showed that among the available alternatives, option A had the highest score and is therefore recommended as the best option for ELML. Overall, the combination of OPA and EDAS methods proved to be effective in facilitating the decision-making process and ensuring that the most suitable alternative was selected based on the defined factors. In the analysis chapter, the effectiveness and accuracy of the proposed method in solving the LML problem will be evaluated by comparing it with other well-known methods documented in the literature.

It's worth noting that in this study, the OPA method was employed solely for scoring the factors, and the alternatives were ranked and scored using the EDAS method. This approach was selected because the study possessed precise information about the alternatives, making the use of a non-compensatory method like EDAS more suitable.

3.2 Phase 2: Problem structure, mathematical modeling

The problem being explored is ELMLP. For designing the mathematical modeling of ELMLP, we use novel vehicle routing modeling with service options, PD, TW and, customer satisfaction. The goal of the problem is to provide service to the customers at minimum cost and maximum level of their satisfaction under operational constraints. Customers are given the option to select between SP or HD, tailored to their preferences, to enhance customer satisfaction (Fig. 2). The issue addressed in this study involves C customers, each having distinct preferences for either delivery or pickup. The presented model is considered in deciding the customers' preferences and provides satisfaction as much as possible.

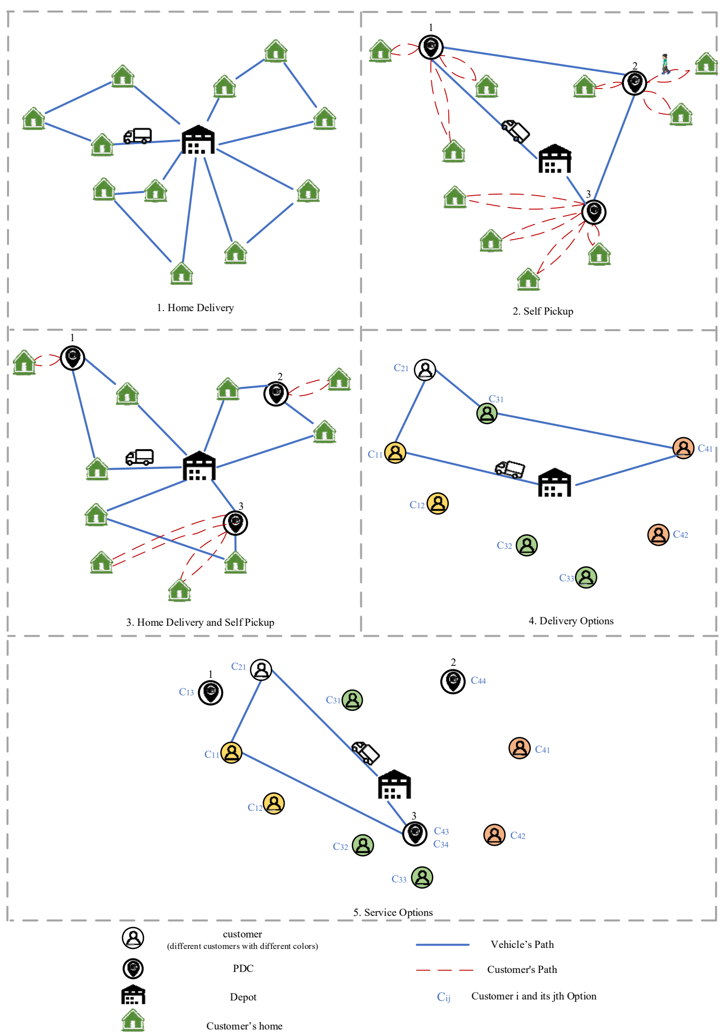

Fig. 2. Graphic representation of various VRP types

Fig. 2 illustrates diverse forms of the VRP, which optimizes vehicle routes to deliver goods or services. The standard VRP, depicted first, uses a single hub, three fixed routes, and eleven demand nodes. The next variation, VRP with self-pickup (VRPSP), incorporates customer pickups from predetermined locations. The third model, VRP with home delivery and self-pickup (VRPHDSP), mixes home deliveries and self-pickups. The fourth type, VRP with delivery options (VRPDOs), allows customers to choose any delivery location. The last variant, VRP with service options (VRPSOs), allows customers to choose their desired method of delivery at different prices, thus requiring route adjustments based on customer choice.

The proposed model is considered in deciding the customers' preferences and provides their satisfaction as much as possible. Because customers are present in different places at different time intervals, service in a specific place should be done in a certain period, which also covers the issue of the hard time window.

There are two types of decisions involved in this problem. The first type of decision is a strategic decision related to selecting PDCs, while the second type is an operational decision related to routing the customer to different locations throughout the day. The purpose of this problem is to identify the locations and optimum costs of pickup points, as well as to determine the routing and sequencing of customer visits with the lowest cost and highest satisfaction.

The model is developed for a distribution company. In this approach, the company also can choose between customer options in order to reduce both the cost and the distance traveled for delivery.

The following are other assumptions included in the model:

- The vehicle fleet is diverse and operates with a specified, limited capacity.
- During each time period, a vehicle services customer once, which ensures their delivery and pick-up demands are met simultaneously.
- Time windows are fixed.
- Each route between delivery centers has a specified travel time.
- Vehicles begin their routes from the hub and return to it after completing their tasks.
- Two types of costs - fixed and variable - are assigned to each vehicle.
- Each vehicle can be used on several tours.
- Customer service time is considered to be average and uniform.
- The duration of the trip is fixed and corresponds to the distance between two points.
- Delivery to one of the options selected by the customer is mandatory.

The developed model is a bi-objective mixed integer mathematical model. Initially, the model begins by outlining the symbols used, which are detailed in Table 4. Following this, a comprehensive description of the model is provided.

Table 4
Indicators, parameters, and variables of VRPSO

Symbol	*Explanation*
Indices	
i,j	Delivery point index
c	Customer index
v	Vehicle index
G	Network, G= (E, A)
E_P	A set of pickup centers
E_C	A set of customer options
E_0	A set of nodes plus the depot
E	A set of nodes
CL	A set of customers
V	A set of vehicles
Parameters	
A_{cj}	The matrix in which all the elements are either 0 or 1 for the presence of the customer
Q_v	The capacity of vehicle V
d_c	Delivery demand of customer
PF_v	The fixed cost of using the vehicle $k=v$

Pr_{cj}	Customer preferences matrix
P_{ij}	The travel cost from i to j
PO	The cost associated with the options selected by the customers
PS	The fee required for customers to avail themselves of the self-pickup service
Q_v	The capacity of vehicle v
CP_j	The maximum handling capacity of node 'j' as a self-pickup center
M	A large number
Variables	
X_{ijv}	Equals 1 when vehicle v travels from node i to location j; 0 in all other cases
U_v	Equal to 1 if vehicle v is used; 0, otherwise
$Zcjv$	Takes the value 1 if customer c receives service at node j through vehicle v; 0, otherwise
D'_{ijv}	The load carried in response to delivery demand by vehicle v as it moves along the arc from node i to j
D''_{ijv}	The load carried in response to pick-up demand by vehicle v as it moves along the arc from node i to j
D_{ijv}	Freight transported by vehicle v that drives through the arc (i, j)

VRPSO Model:

The VRPSO is formulated based on a graph G = (E, A), representing the network it operates within. Here, $E_0 = \{0\} \cup E_P$ is indicative of the depot being represented by the numeral 0, while $E_P = \{1, ..., e_p\}$ corresponds to the collection of PPs. A signifies the set of arcs and is represented as $A = \{(i, j): i, j \in V\}$, where P_{ij} denotes the cost associated with the arc $(i, j) \in A$. Notably, this cost is predetermined and remains constant. Each customer, denoted by c, possesses a specific demand ($d_c \geq 0$) that mandates fulfillment through one of the available SOs. The vehicles engaged in the logistics operations initiate their routes at the depot and are required to culminate their journeys back at the same point. Essentially, this framework establishes a comprehensive structure to model the routing of vehicles to efficiently serve customers with different service preferences, while commencing and concluding their routes at a central depot.

Using the information provided above, the model for the VRPSO can be expressed in the following:

$$\min\ Z_1 = \left(\sum_i \sum_j \sum_v (P_{ij} \times X_{ijv}) + \sum_v (PF_v \times U_v)\right) - \sum_c \sum_{j \epsilon E_p} \sum_v (PS \times Z_{cjv}) - \sum_c \sum_{j \epsilon E_H} \sum_v (PO \times Z_{cjv}) \quad (1)$$

$$\max\ Z_2 = \sum_c \sum_j Z_{cjv} \times Pr_{cj} \quad (2)$$

$$\sum_j \sum_v A_{cj} \times Z_{cjv} = 1 \qquad \forall c \epsilon CL \quad (3)$$

$$\sum_i X_{ijv} = \sum_i X_{jiv} \qquad \forall i \neq j, j \epsilon E, v \epsilon V \quad (4)$$

$$\sum_{i \in E} X_{0iv} = \sum_{j \in E} X_{j0v} \qquad \forall\ v \epsilon V \quad (5)$$

$$D_{ijv} \leq X_{ijv} \times Q_v \qquad \forall\ v \epsilon V, i, j \epsilon E \quad (6)$$

$$\sum_c Z_{cjv}.CL \leq \sum_{i \in E0} X_{ijv} \qquad \forall j \epsilon E, v \epsilon V \quad (7)$$

$$\sum_c \sum_v Z_{cjv} \leq Cp_j \qquad \forall\ j \epsilon E \quad (8)$$

$$\sum_i \sum_j X_{ijv} \leq M \times \sum_j X_{0jv} \qquad \forall\ v \epsilon V \quad (9)$$

$$\sum_i D_{ijv} \leq \sum_c d_c \times Z_{cjv} + \sum_i D_{jiv} \qquad \forall j \epsilon E, v \epsilon V \quad (10)$$

$$\sum_{j \in E} D_{1jv} = \sum_c d_c \times \sum_c \sum_j d_c \times Z_{cjv} \qquad \forall\ v \epsilon V \quad (11)$$

$$\sum_j D_{j0v} = 0 \qquad \forall\ v \epsilon V \quad (12)$$

$$\sum_i X_{ijv} \leq M \times U_v \qquad \forall\ v \epsilon V \quad (13)$$

$$Y_{iv} - Y_{jv} + CL \times X_{ijv} <= CL - 1 \qquad \forall i \neq j, i, j \epsilon E, v \epsilon V \quad (14)$$

$$X_{ijv} = \{0,1\} \qquad \forall i, j \epsilon (E), j \epsilon E, v \epsilon V \quad (15)$$

$$Z_{cjv} = \{0,1\} \qquad \forall i, j \epsilon (E), v \epsilon V, c \epsilon C \quad (16)$$

$$U_v = \{0,1\} \qquad v \epsilon V \quad (17)$$

In Eq. (1), the objective function is outlined, aiming to minimize the sum of fixed and variable costs associated with the use of vehicles and the opening of PDCs, as well as maximize the income of delivery services. Eq. (2) is the second objective function and aims to increase customer satisfaction. Eq. (3) confirms that every customer receives service at one time only. Eq. (4) mandates that a vehicle must exit a location once it has arrived. Eq. (5) is a provision ensuring that a vehicle returns to the depot if it departs from it. Eq. (6) assures compliance with each vehicle's capacity for all arcs, maintaining the flow. Eq. (7) dictates that a vehicle will not make a trip to a place where there are no deliveries to be made. Eq. (8) guarantees that the capacity of PDCs is restricted. Eq. (9) dedicates that vehicles are required to depart the depot before they are put into use. Eq. (10) to Eq. (12) enforce the correct flow of vehicles. The utilization of specific vehicles is indicated by Eq. (13). Eq. (14) prevents the occurrence of sub-tours. Lastly, Eq. (15) to Eq. (17) depict binary and positive variables.

VRPSO with pickup and delivery (VRPSOPD) formulation:

The next formulation proposed in this article is the pick-up and delivery formulation for VRPSO. In this modeling, in addition to the parameters and variables of model VRPSO, variable p_c and parameters D'_{ijv} and D''_{ijv} have also been used. The definitions of new parameters, variables, and constraints for PD formulation are explained in the following (Table 5).

Table 5
The parameters and variables of VRPSO with pickup and delivery

D'_{ijv}	Transportation of delivery demand via arc (*i*,*j*) by vehicle *v*
D''_{ijv}	Transportation of pickup demand via arc (*i*,*j*) by vehicle *v*
P_c	Pickup demand of customer *c*

$$D'_{ijv} + D''_{jiv} = D_{jiv} \qquad \forall i, j \in E, v \in V \tag{18}$$

$$\sum_i D'_{ijv} \le \sum_c d_c \times Z_{cljv} + \sum_i D'_{jiv} \qquad \forall j \in E, v \in V \tag{19}$$

$$\sum_i D''_{ijv} \le -\sum_c p_c \times Z_{cjv} + \sum_i D''_{jiv} \qquad \forall j \in E, v \in V \tag{20}$$

$$\sum_v \sum_j D''_{0jv} = 0 \tag{21}$$

$$\sum_v \sum_j D''_{j0v} = \sum_c p_c \tag{22}$$

$$\sum_v \sum_j D'_{0jv} = \sum_{cl} d_{nc} \tag{23}$$

$$\sum_v \sum_j D'_{j0v} = 0 \tag{24}$$

Eq. (18) illustrates that the complete freight carried will be the combined total of deliveries and pickups over a given arc. Eq. (19) and Eq. (20) are responsible for the revision of the flow related to PD demands. Eq. (21) to Eq. (24) indicate that parcels are loaded and unloaded at the start and end of each route.

VRPSOPD with Time windows (VRPSOPDTW):

In Table 6, we define the parameters and variables that need to be added to the first formulation for the time windows constraint, so the model is called VRPSOPDTM. In this model, each customer has a TW in order to choose his options that is shown by [St_{nj},Ft_{nj}]. We assume that these TWs are fixed, and the delivery must happen on time.

Table 6
Parameters and the variable of VRPSOPD with time window

Parameters	
ds_i	The service duration in location i
t_{ij}	Travel time between points i, j
St_{cj}	The start time of customer c presence at point j
Ft_{cj}	The finish time of customer c presence at point j
Decision variable	
S_{jv}	The start time of servicing point j by vehicle v

$$\sum_{cl} Z_{clvj} \times St_{clj} \leq S_{jv} \leq \sum_{cl} Z_{clvj} \times Ft_{clj} \qquad \text{j} \in Home\ delivery\ \forall \qquad (25)$$

$$S_{jv} + ds_j + t_{ji} - M_{ji}(1 - X_{jiv}) \leq S_{iv} \qquad \text{j}, i \in E\ , v \in V\forall \qquad (26)$$

Eq. (25) states the start time of servicing point j must be within the allowed TW. Eq. (26) indicates the arrival time to point i should be more than the arrival time at the past location plus the duration of travel between those; this equation ensures that the time flow is correct.

4. Case Study and Solution Methodology

This paper presents a case study of applying an ELML model to enhance delivery operations in a Tehran marketplace. Initially reliant on a single-depot delivery system, the company aims to adopt ELML strategies to cut costs and improve customer satisfaction. The model's practical implementation involves a two-phase decision-making process, focusing on selecting optimal PDCs and optimizing vehicle routing, considering SOs like self-pickup and home delivery. Utilizing OPA and EDAS methods for strategic PDC selection and an optimization model coupled with the NNC method for operational vehicle routing, the study showcases the model's effectiveness in informing smarter LML decisions.

Based on expert opinion and the availability of the customer's data under study, the analysis spans various configurations, including 4-30 customers, 1-3 vehicles, 7 PDCs, two pricing tiers, four time periods, and three delivery scenarios: HD, HD and Self-Pickup (HDSP), and Service Options (SO).

4.1 Selecting pickup and delivery centers (PDCs) (strategic decision):

This section delineates the process of selecting PDCs for ELML, employing a two-pronged approach: firstly, leveraging OPA method to weigh critical factors in PDC selection, and secondly, utilizing the evaluation based on EDAS method for ranking alternatives. The OPA method aids in discerning pivotal decision-making factors by attributing weights according to their importance, thus highlighting the most critical elements for PDC selection. Subsequently, the EDAS method ranks these alternatives by evaluating their performance against the weighted factors. Collectively, this comprehensive approach integrates OPA and EDAS to facilitate informed strategic decisions in PDC selection, emphasizing the identification and prioritization of key factors, followed by a performance-based ranking of potential alternatives.

4.1.1 Application of OPA

The methodology depicted in Fig. 2 was put forward and implemented within the marketplace sector in Tehran city to assess the influence of the factors on the PDCs. Initially, a panel of 6 specialists was gathered and surveyed to offer their ordinal evaluations for the factors. To improve the accuracy of the judgments, the experts were ranked due to their varying expertise and experience.

Then, each expert was asked to evaluate the factors based on their relative importance using ordinal numbers. This method was employed to allow the specialists to convey their evaluations on the significance of each criterion grounded in their individual knowledge and experience. To ensure that the important rankings were as accurate as possible, each expert was asked to provide a separate evaluation of the factors. Following the finalization of the research factors presented in Table 2, the weight of each factor was determined through the OPA method, considering the expert's opinions. The subsequent stage involved the development of a mathematical model that calculated the weights of the factors using the experts' rankings, as well as their preferences on research factors (Table 7).

Table 7
OPA-based factors weighting

Factor	Weight	Rank
F_1	0.2207423	1
F_3	0.2034290	2
F_2	0.1997372	3
F_6	0.1376131	4
F_4	0.0833581	5
F_7	0.0670996	6
F_5	0.0349812	7
F_8	0.0283629	8
F_9	0.0246766	9

Once the weights of the factors were determined through the OPA method, the EDAS approach was employed for ordering the alternatives.

4.1.2 Application of EDAS

In this section, a set of five potential delivery centers is identified as available options. The evaluation of these options will be conducted in this section using the EDAS method and the weights derived by OPA. In the EDAS method, the decision matrix X is presented in Table 8. The last row of the table represents average value (AV) for each criterion.

Table 8
EDAS decision matrix and AV values

Factors	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9
OPA Weight	0.221	0.200	0.203	0.083	0.035	0.138	0.067	0.028	0.025
Type	MAX	MAX	MAX	MIN	MIN	MIN	MIN	MIN	MIN
Alternative	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9
A_1	105	0.5	0.8	0.1	0.1	0.6	0.4	0.2	1
A_2	144	0.4	0.7	0.2	0.2	0.4	0.4	0.3	1
A_3	144	0.6	0.8	0.3	0.3	0.5	0.3	0.1	1
A_4	40	0.3	0.9	0.1	0.1	0.3	0.5	0.8	2
A_5	48	0.9	0.6	0.2	0.3	0.7	0.2	0.2	1
AV	96.2	0.54	0.76	0.18	0.2	0.5	0.36	0.32	1.2

The results of EDAS, as detailed in Table 9.

Table 9
The results of EDAS

	SP^3_i	SN^4_i	NSP^5_i	NSN^6_i	AS^7_i	RANK
A_1	0.100	0.050	0.564	0.836	0.700	3
A_2	0.143	0.085	0.805	0.721	0.763	2
A_3	0.177	0.073	0.998	0.759	0.878	1
A_4	0.147	0.303	0.827	0.000	0.414	5
A_5	0.178	0.235	1.000	0.223	0.612	4

The table presented the conclusive outcomes derived from the OPA-EDAS methodology employed to identify the optimal PDC among a set of five alternatives. As per the findings, Alternative A_3 possesses the highest aggregated score ($AS_3 = 0.878$), securing its first-place rank and establishing it as the most suitable PDC according to the OPA-EDAS method. Subsequently, Alternative A_2 occupies the second position with an AS_2 of 0.763, followed by A_1 ($AS_1 = 0.700$), A_5 ($AS_5 = 0.612$), and A_4 ($AS_4 = 0.414$). The culmination of this phase yields a collection of parameters, which serve as the input for the optimization model employed in the subsequent phase, thus facilitating a seamless progression toward the final solution.

4.2 Optimal route and PDCs allocation (operational decisions):

This study introduces an expanded version of the VRP. We made use of IBM's ILOG CPLEX Optimization Studio (version 12.6) to tackle the problem, operating on a computing setup endowed with an Intel Core i5 processor at 2 GHz and 16 GB of RAM, and experimented across multiple scales. As per our extensive survey, there appears to be an absence of any dataset in the existing literature that closely aligns with the research proposition we present, which we refer to as VRPSO. The spatial arrangement of both PDCs, including the depot, is randomly allocated within a square grid with axes ranging from 0 to 1000 units, based on the uniform distribution, as cited by (Hasanpour Jesri et al., 2022). Moreover, the evaluation of routing expenses is done through the calculation of Euclidean distances, making use of the EUC_2D function as defined in TSPLIB (Reinhelt, 2014). An in-depth analysis of the outcomes yielded by the model is set to follow in the sections ahead.

As highlighted previously, the proposed model integrates two objective functions. In solving bi-objective mathematical models such as ELMLSO, there is a myriad of methods that can be employed. Common approaches include the Weighted Sum Method, where various weights are assigned to the objectives and then summed to form a single objective function (Marler and Arora, 2010); the Epsilon Constraint Method, which involves optimizing one of the objectives while the others are restricted to certain threshold values; and Goal Programming, which aims to minimize the deviation from desired levels for multiple objectives (Charnes & Cooper, 1977). However, these traditional methods often do not efficiently explore the entire Pareto frontier, which is essential in capturing the trade-offs between the objectives in VRPSOs. The NNC method is preferred for its ability to systematically generate a well-distributed set of Pareto optimal solutions, covering the entire Pareto frontier without requiring prior knowledge of its shape or properties. This capability is vital for offering decision-makers a comprehensive array of alternatives, showcasing the inherent trade-offs between objectives. Thus, NNCM's adoption in this study underscores its effectiveness in addressing the bi-objective nature of VRPSOs, facilitating diverse and informed decision-making.

[3] The score of positive distance
[4] The score of negative distance
[5] Normalized SP
6 Normalized SN
[7] Appraisal score

The NNCM commences by solving the model to attain anchor points through the separate optimization of each objective function. This is followed by employing Utopia and Nadir points as tools for rendering these functions normalized. The process then establishes a Utopia Line (UL) and normalized increments for the assembly of Pareto frontiers. It is pertinent to note that scenarios, the NNC method may yield non-Pareto solutions; thus, to counteract this, the Pareto Filter algorithm is deployed to expunge any such non-Pareto solutions from the set of generated solutions. Comprehensive elucidation on this process will be provided in the discussions that follow.

Based on the methodology described above, the objective functions can be represented in their normalized form as follows:

As per the described method, the objective functions are converted into a normalized form. In this scenario, the model is independently solved for both objective functions 1 and 2 (W_1 and W_2). Consequently, y_1* and y_2* represent the solution vectors associated with W_1* and W_2*, respectively. Following the method, the objective values are normalized ($\overline{ww_1}$ *and* $\overline{ww_2}$) and connected by a line referred to as the utopia line (Fig. 3).

$$\bar{F} = \left\{ \frac{W_1(y) - W_1(y_1^*)}{W_1(y_2^*) - W_1(y_1^*)} \; \frac{W_2(y) - W_2(y_2^*)}{W_2(y_1^*) - W_2(y_2^*)} \right\} \tag{27}$$

Furthermore, according to the method's factors, the NNCM generates Pareto points along the direction of the UL:

$$\bar{N} = \overline{W_2}^* - \overline{W_1}^* = [1,0] - [0,1] = [1,-1] \tag{28}$$

As a result, by segmenting the UL into 25 parts (where g denotes the number of solutions), and adjusting two weights $0 \leq \phi_{1,g}, \phi_{2,g} \leq 1$, with the constraint $\phi_{1,g} + \phi_{2,g} = 1$, using a step size of $\gamma = 1/(g-1)$, solutions are obtained by evaluating a series of uniformly spaced points along the Utopia line:

$$\bar{Y}_g = \phi_{1,g} \overline{W_1}^* + \phi_{2,g} \overline{W_2}^* \tag{29}$$

In order to find each solution, $\phi_{1,g}$ increases by the value of gamma along the Utopia Line, while the weight decreases by one step. In this problem, 25 solutions were generated, with each step having a value of 1/24. By solving the subsequent sub-problem with the added normal constraint, Pareto solutions are derived using the following model:

$$min_y \, \overline{W_2} \tag{30}$$

Subject to Eq. (30) and $\overline{N(W - \bar{Y}_g)}^T \leq 0$ as a normalized constraint.

In compliance with the guidelines of the NNC method, a minimization format must be employed. The outcomes of resolving the transformed model for each objective function, alongside the computed distances, are presented in Table 10. The NOF[8] can be found in Eq. (31) and Eq. (32). The UL and Pareto frontier for the model are depicted in Fig. 3.

Table 10
Objective functions value for each objective function and distances between solutions

Optimal Decision Points	Value of Eq. (1)	Value of Eq. (2)
y_1^*: Optimum decision for objective 1	2836	-14
y_2^*: Optimum decision for objective 2	3880	-40
L: Distance between solutions	1044	26

In accordance with the methodology described above, the NOF is as follows:

$$\overline{W_1} = \left(\left(\sum_i \sum_j \sum_k (C_{ij} \times X_{ijk}) + \sum_r (CF_k \times U_k)\right) + \left(\sum_n \sum_{j \epsilon E_p} \sum_k (P_P \times Z_{njk}) + \sum_n \sum_{j \epsilon E_H} \sum_k (P_H \times Z_{njk})\right)\right) - 2836/1044 \tag{31}$$

$$\overline{W_2} = \left(\left(-\sum_i \sum_j Z_{njk} \times P_{nj}\right) - (-40)\right)/ 26 \tag{32}$$

[8] Normalized Objective Function

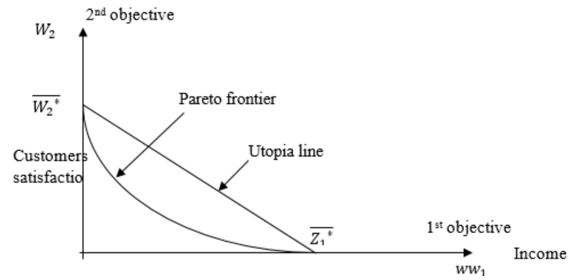

Fig. 3. The Pareto frontier and UL for model

Using the NNC method, we produced 25 outcomes (g=25) for the optimization model by the NNCM, incrementing the weights by a factor of 1/24 ($\gamma = \frac{1}{25-1}$). In order to identify the dominant points within the solution set, we employed the Pareto filter algorithm, following the methodology delineated by (Messac & Mattson, 2004) , and ultimately, we retained 16 Pareto points (Table 11). Nine of the initially generated outcomes were removed from the Pareto solutions because one point was considered superior to another, warranting its removal from the Pareto set. The curve representing the Pareto optimal solutions for the mathematical model defined by Eq. (30) through Eq. (31) is depicted in Fig. 4.

Table 11
Acquired Solutions within the Pareto Optimal Frontier

Solution	$\overline{W_1}$	Profitability objective value	$\overline{W_2}$	Customer satisfaction objective value
1	0.037356	2875	0.961538	-15
2	0.069923	2909	0.923077	-16
3	0.128352	2970	0.846154	-18
4	0.187739	3032	0.769231	-20
5	0.198276	3043	0.730769	-21
6	0.237548	3084	0.692308	-22
7	0.245211	3092	0.653846	-23
8	0.269157	3117	0.615385	-24
9	0.274904	3123	0.538462	-26
10	0.285441	3134	0.461538	-28
11	0.487548	3345	0.384615	-30
12	0.502874	3361	0.346154	-31
13	0.611111	3474	0.269231	-33
14	0.637931	3502	0.192308	-35
15	0.681992	3548	0.115385	-37
16	0.888889	3764	0.038462	-39

Fig. 4. Pareto Frontier for Bi-objective Optimization for VRPSO

The depicted figure illustrates the trade-off between profitability ($\overline{W_1}$) and customer satisfaction ($\overline{W_2}$) based on various configurations of the LML strategy. On the horizontal axis, we have profitability values, and on the vertical axis, customer satisfaction values. High customer satisfaction corresponds to lower profitability, indicating scenarios where a business heavily prioritizes customer demands. Conversely, as profitability increases, customer satisfaction decreases, suggesting a focus on operational efficiency and cost reduction that might compromise certain aspects of customer satisfaction. This downward trend from high satisfaction and low profitability to low satisfaction and high profitability underscores the balancing act necessary for businesses. It serves as a visual guide to understanding this delicate interplay between key objectives in the implementation of LML strategies.

5. Sensitivity analysis

Within the scope of this section, an extensive sensitivity analysis is carried out to assess the resilience and reliability of the LML model that we have proposed. Undertaking this analysis is imperative as it sheds light on the model's equilibrium and efficacy when subjected to a spectrum of scenarios and alterations in the parameters. Such an understanding is essential for gauging the model's adaptability and responsiveness to changing conditions and requirements.

For the sensitivity analysis, in order to examine the influence, we arranged six groups with three distinct instance scales, specifically 6, 10, and 14 customers. Within each group, we juxtapose two varied scenarios as delineated below, and the Pareto front solutions are illustrated in Table 12.

(i) Scenario 1: In each instance, merely 50% of customers possess specific delivery time demands, while the remainder can be catered to at any point within the entire planning period. For the 50% of customers who do not choose a specific time period, their satisfaction is assumed to be determined by an average satisfaction level. This average satisfaction level is considered their priority in the overall planning to ensure a balanced approach to meeting customer preferences.

(ii) Scenario 2: In every instance, all customers bear particular delivery time requirements that correspond with their preferences.

Table 12
Pareto solutions of two scenarios

SCENARIO	1						2					
CUSTOMER	6		10		14		6		10		14	
OBJECTIVE	W_1	W^*_2	W_1	W_2	W_1	W_2	W_1	W_2	W_1	W_2	W_1	W_2
PARETO SOLUTIONS												
1	2251	-2.50	3210	-1.90	4406	-1.71	1854	-2.17	2875	-1.50	3705	-1.43
2	2280	-2.67	3290	-2.10	4522	-1.86	1895	-2.33	2909	-1.60	3760	-1.50
3	2347	-2.83	3384	-2.20	4614	-1.93	1954	-2.50	2970	-1.80	3869	-1.57
4	2512	-3.00	3407	-2.30	4656	-2.00	2010	-2.67	3032	-2.00	3952	-1.71
5	2495	-3.17	3521	-2.40	4718	-2.07	2083	-2.83	3043	-2.10	3990	-1.79
6	2665	-3.33	3597	-2.50	4799	-2.14	2137	-3.00	3084	-2.20	4025	-1.86
7	2624	-3.50	3674	-2.60	4825	-2.21	2195	-3.17	3092	-2.30	4046	-1.93
8	2727	-3.67	3745	-2.70	4955	-2.29	2226	-3.33	3117	-2.40	4067	-2.00
9	2656	-3.83	3833	-2.80	4999	-2.36	2242	-3.50	3123	-2.60	4134	-2.14
10	2688	-4.00	3910	-2.90	5093	-2.43	2290	-3.67	3134	-2.80	4202	-2.29
11	2791	-4.17	3982	-3.00	5157	-2.50	2320	-3.83	3345	-3.00	4350	-2.43
12	2969	-4.33	4048	-3.10	5220	-2.57	2391	-4.17	3361	-3.10	4426	-2.57
13	2980	-4.50	4147	-3.30	5352	-2.64	2420	-4.33	3474	-3.30	4566	-2.79
14	3069	-4.67	4230	-3.40	5500	-2.71	2474	-4.67	3502	-3.50	4608	-2.93
15	3028	-4.83	4301	-3.50	5692	-2.86	2524	-5.00	3548	-3.70	4730	-3.07
16	3167	-5.00	4387	-3.60	5891	-3.00	2599	-5.33	3764	-3.90	4942	-3.21
AVERAGE	2703	-3.75	3792	-2.77	5025	-2.33	2226	-3.53	3211	-2.61	4211	-2.20

*To investigate the impact of varying customer numbers, the value of W_2 objective function is divided by the total number of customers. This division allows for the analysis of how changes in the number of customers affect various performance measures and outcomes

In the sensitivity analysis, our study reveals significant insights regarding the influence of customers' choices on operational costs and overall satisfaction levels in the LML model. It was observed that as a greater number of customers opted for diverse locations for receiving service, the operational costs for the company were considerably reduced. This phenomenon can be attributed to the expanded feasible region, which allows the model to optimize the routes and delivery centers more effectively, thereby enhancing the efficiency of the delivery process.

Interestingly, the increase in the diversity of customer choices for service reception locations also led to a slight improvement in customer satisfaction levels. This can be ascribed to the greater degree of customization and flexibility that can be provided in the delivery process, better catering to individual customer preferences, and convenience. However, it is crucial to highlight that the impact of the number of customers choosing different options on the overall satisfaction levels was relatively minor compared to its effect on the operational costs.

These findings underline the critical value of customers actively participating in this approach. The more customers participate in the policy, the better the outcomes in terms of cost optimization and customer satisfaction. The proposed bi-objective model provides an effective tool for businesses to balance minimizing costs and maximizing customer satisfaction in their delivery operations.

Fig. 5 illustrates a sensitivity analysis of the LMLSO model under two different scenarios for varying numbers of customers and options for service. The solid line represents Scenario 1, where only 50% of customers have specific delivery time demands. On the other hand, the dotted line corresponds to Scenario 2, where all customers have specific delivery time preferences.

A significant observation is noted when examining the effects of available SOs on total costs. There is a substantial decrease in total cost as the number of available SOs increases from home delivery to 4 extra options. The most pronounced reductions are observed when introducing the first and second SOs. Beyond these, while the costs continue to decrease as more options are added, the rate of cost reduction starts to diminish. This point emphasizes the substantial impact that providing even a few SOs can have on efficiency and cost-effectiveness.

In comparison between scenarios, Scenario 2 consistently incurs a lower total cost than Scenario 1 for the same number of customers and options. This suggests that when all customers have specific delivery time preferences, it could potentially lead to a more streamlined and cost-effective operation. This might be due to the ability to plan and optimize routes more efficiently based on known delivery times.

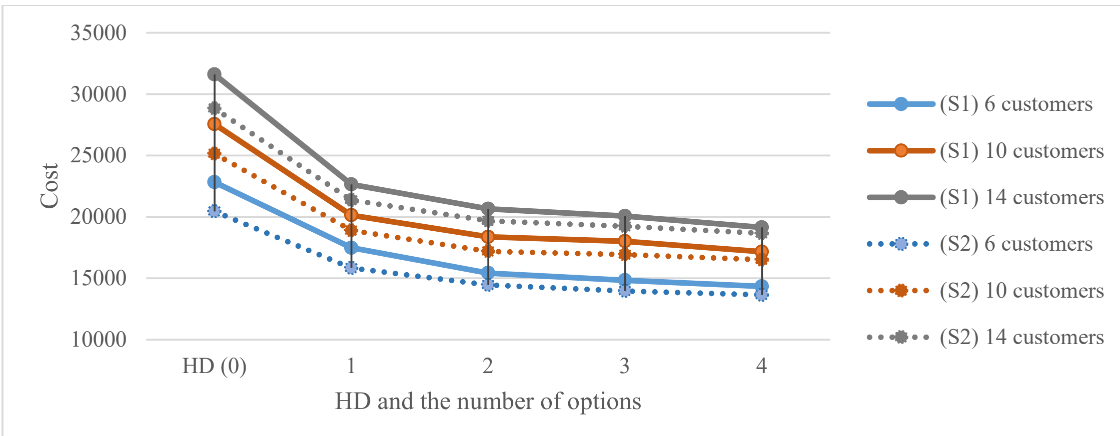

Fig. 5. Variation in Travel Costs and Its Influence on the Quantity of Chosen Options across Various Scenarios

Overall, this analysis underscores the importance of strategic planning in LML operations, taking into account the number of customers, their preferences, and the available service options (at least one option). It also shows how different scenarios can impact the total operational cost, providing valuable insights for decision-making.

In the process of enhancing delivery efficiency, selecting optimal PDCs plays a crucial role. The choice of these locations can significantly impact operational costs and customer satisfaction. To identify the most appropriate PDC, it is necessary to employ a multi-criteria decision-making approach that evaluates a variety of significant factors. In the following analysis, a comparative examination of five methods, namely OPA-EDAS, SWARA-COCOSO, SWARA-EDAS, OPA-COCOSO, and OPA, is conducted. Each method provides a unique analytical framework to assess potential PDCs—A_1, A_2, A_3, and A_4. This comparative study offers a robust mechanism for cross-validating the results, ensuring the reliability and accuracy of the location selection process. Table 13 showcases the final scores and rankings achieved through each method, leading to an overall ranking.

Table 13
Analyzing Ranking Differences Among MCDM Techniques for PDCs

PDC	OPA-EDAS		SWARA-EDAS		SWARA-COCOSO		OPA-COCOSO		OPA		Overall Ranking
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	
A_1	0.700	3	0.686	3	2.594	2	2.445	3	0.209	3	3
A_2	0.763	2	0.756	2	2.558	3	2.459	2	0.277	2	2
A_3	0.878	1	0.894	1	2.716	1	2.570	1	0.325	1	1
A_4	0.414	5	0.330	5	1.444	5	1.444	5	0.098	4	5
A_5	0.612	4	0.608	4	1.912	4	1.849	4	0.088	5	4

Upon examining the results showcased in Fig. 6, it becomes evident that PDC A_3 consistently outperforms the rest, securing the top rank across all evaluation methods. This consistency underscores A_3 as the optimal choice for a location across the various analytical models applied. In contrast, PDC A_4 consistently finds itself at the bottom of the rankings, indicating it is a less favorable choice for a location. The other PDCs, A_1 and A_2, secure intermediate positions, although A_2 tends to score slightly higher than A_1. This analysis lends credence to the reliability of the OPA-EDAS model in the context of PDC selection. It thus becomes an instrumental tool in aiding decision-making, enhancing its precision and reliability.

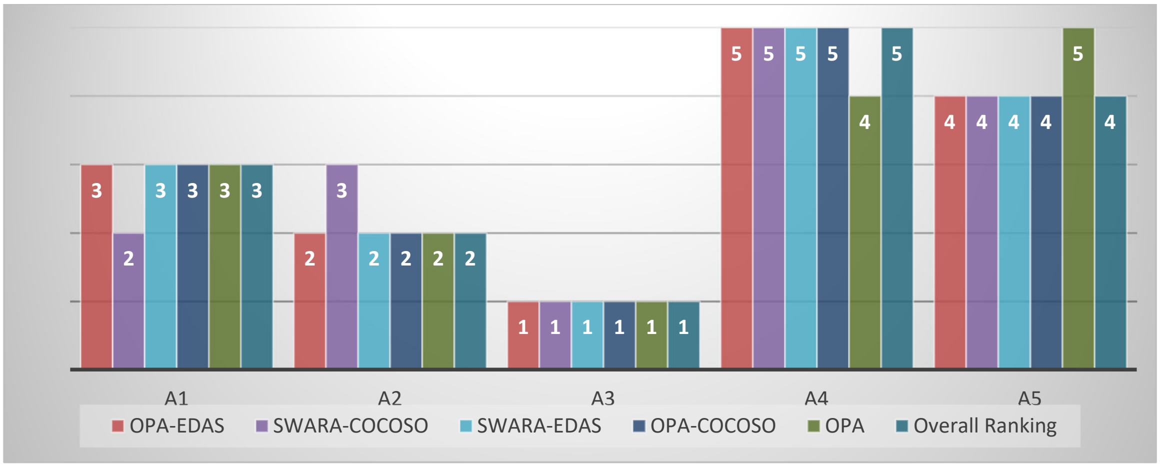

Fig. 6. Comparison of the OPA-EDAS approach with other MCDM methods

6. Managerial insight

The novel two-phase methodology presented in this study provides several practical implications that can aid managers in the effective application of ELMLSO. The findings derived from this research can serve as valuable guidance for decision-making and strategic actions.

- The observations derived from the initial phase of the methodology underscore the importance of focusing on two pivotal criteria - availability and accessibility - and suggest that managers should accord high priority to these aspects during the decision-making process for selecting delivery centers. This means ensuring that these centers are conveniently located and easily reachable for customers, and that they consistently provide reliable services. By focusing on these key aspects, the company can significantly enhance customer satisfaction and loyalty.
- Customer Participation is Key to Operational Efficiency: The findings from the sensitivity analysis shed light on the pivotal role customer participation plays in optimizing operational costs in a LML model. As a larger pool of customers chooses varied locations for service reception, the company experiences a notable reduction in operational costs. This indicates that customers' active participation in determining the delivery locations allows the model to better optimize the routes and delivery centers, thereby enhancing delivery efficiency. Hence, businesses should aim to foster such active participation and offer more choices to customers in the delivery process.
- Diverse Choices Improve Customer Satisfaction: The study also uncovers that an increase in the diversity of customer choices for delivery locations contributes to a slight improvement in customer satisfaction levels. Despite the impact being relatively minor compared to the effect on operational costs, this aspect underscores the importance of customization and flexibility in delivery operations. By accommodating individual customer preferences and convenience, businesses can subtly boost satisfaction levels, resulting in improved customer loyalty over time. Therefore, the strategic integration of varied delivery options can serve as a powerful tool for businesses to elevate customer satisfaction while optimizing costs in their delivery operations.
- An essential insight from the analysis is the considerable influence that the introduction of the first and second service options has on reducing costs. These initial alternatives appear to have the most substantial impact on efficiency and cost-effectiveness. Interestingly, while costs continue to decline as more options are added, the rate of this reduction starts to taper off after the second option. Therefore, managers should place a particular focus on ensuring at least a couple of diverse, well-planned service options are available. Even these few alternatives can lead to significant improvements in operational efficiency and substantial cost savings. This insight underlines the idea that the strategic implementation of service options can lead to optimized performance in LML operations.

7. Conclusion and future research

The persistent escalation in e-commerce activities coupled with the burgeoning demand for doorstep deliveries is exerting tremendous pressure on logistics systems, leading to an upward spiral in the cost of daily customer deliveries. In response to these challenges, this paper has proffered a tailor two-phase methodology integrating an MCDM framework with mathematical modeling. This innovative methodology effectively addresses the optimization of the LMLSO under consideration of PD services and TWs.

In the first phase of the study, we applied the OPA-EDAS method to determine the most suitable PDCs, considering several critical criteria. The second phase pivots to the identification of optimal routes using a bi-objective mixed-integer mathematical model, striking a balance between minimizing logistical costs and maximizing customer satisfaction. The introduction of various services and variable-priced deliveries further enhanced the versatility and adaptability of this approach.

The study reveals critical factors that can enhance the efficiency and cost-effectiveness of LML operations. These include prioritizing the availability and accessibility of delivery centers, fostering active customer participation in delivery choices, and providing diverse delivery options. Interestingly, the introduction of the first service option led to significant cost reductions, with diminishing returns observed with subsequent options. These insights suggest that strategically offering diverse delivery choices and promoting active customer involvement can significantly improve operational efficiency and customer satisfaction in LML problems.

Future research could benefit from incorporating stochastic or robust optimization techniques into the proposed model. This would enable the model to consider and respond to the inherent uncertainty and variability in the parameters, potentially leading to more resilient and adaptable delivery strategies. The model proposed in this study assumes static demand and does not consider how changes in the price of service could influence customer decision-making and overall demand. Future research could address this by developing multi-level models that consider the company and customers as decision-makers in a leader-follower relationship. By simulating how changes in delivery service prices might influence customer preferences and behaviors, these multi-level models could provide more nuanced insights and enable more strategic pricing decisions in LML.

Data Availability

Data will be made available on request.

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