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Survey

A literature review of collaborative truck and drone in last-mile delivery

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ABSTRACT

The rapid growth of e-commerce and environmental factors have had a major impact on logistics companies, forcing them to improve their delivery systems. Although drone delivery provides a solution to obstacles on the ground, its sole implementation is hindered by some limitations, and the integration of drones with trucking methods provides a solution to overcome the limitations. This paper focuses on 15 literature reviews and 144 research articles on the topic of collaborative trucks and drones in last mile delivery (CTD-LMD). First, an overview of the recent literature reviews is provided based on their classifications and future directions. Then, this delivery problem is categorized into three categories and the factors and objectives of each category are discussed. In addition, the approaches are categorized based on how the studies have addressed the challenges of CTD delivery problems. Despite the great interest in this modern delivery system, there are still many challenges that need to be overcome to fully develop this innovative delivery system. Through analysis, this literature review identifies the gaps in existing studies and provides directions for future studies to improve the performance of integrated truck and drone delivery systems. In conclusion, the report suggests that despite many obstacles, CTD can improve the efficiency of last-mile delivery systems and reshape the future of logistics.

1. Introduction

E-commerce has made considerable progress in recent decades. In 2023, retail e-Commerce will reach almost 5.8 trillion US dollars worldwide. This growth is predicted to increase by more than 39% in the coming years and is expected to reach over 8 trillion dollars by 2027 (Chevalier, 2024). This remarkable boom in e-Commerce brings with it numerous challenges for last-mile delivery, which must be managed efficiently in order to provide cost-effective and high-quality services. According to the Parcel Shipping Index Annual Report (Bowes) The US parcel volume is forecast to reach between 23 billion and 35 billion parcels by 2029.

Last-mile delivery is highly dependent on transportation vehicles, which vary according to customer demand. Traditional delivery vehicles such as vans and trucks are preferred for delivering goods of different shapes and sizes due to their capacity and versatility, but small cars, motorcycles, and scooters, which consume less fuel, are also well suited for delivering smaller items, especially in heavy traffic. Small and environmentally friendly vehicles such as bicycles and cargo bikes also have a remarkable impact on the cost of last-mile delivery, as they do not consume fuel and can avoid traffic jams. In addition, electric vehicles have become very popular with logistics companies due to the decrease in fuel costs and carbon emissions. However, autonomous vehicles such as robots and self-driving delivery vehicles are the future of last-mile delivery vehicles in logistics companies, as they reduce labor costs and increase efficiency. Recently, drones are being considered by logistics companies as a last mile delivery vehicle due to their fast and environmentally friendly delivery capabilities. Advances in drone technology have been increasing and have the potential to be used in a variety of fields, such as medical product transportation (Zailani et al., 2020), surveillance (Ramachandran & Sangaiah, 2021), wireless communication support (Alsamhi, Ma, Ansari, & Gupta, 2019), agriculture (Hafeez et al., 2022), parcel delivery and so on. Delivery by drone is attractive for logistics service providers due to its numerous advantages. Drones can speed up delivery (since drones are faster than ground vehicles) without getting stuck in traffic jams, which is a major challenge in last mile delivery. In general, drones are more flexible and environmentally friendly (as they produce fewer pollutant emissions), require less maintenance than conventional vehicles, and can deliver parcels to inaccessible locations. In addition, drones can play an important role in certain situations, for example, during the coronavirus (COVID-19) pandemic (Mohsan et al., 2022) drones can deliver parcels or medical items to people in quarantine or to patients with chronic diseases to prevent further spread.

There are some limitations for drones, such as battery life, capacity (they can carry small and light packages), weather conditions, flight

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(a) [1]



(b) [7]

Fig. 1. Amazon, Walmart.

zone, flight range limitation, flexibility, and scalability; however, integrated drones and trucks are offered to overcome these challenges. For long distances, trucks bring the drones to specific locations, and the drones take off to deliver the parcels. With this system, the flight range of the drone can be extended. Since trucks, unlike drones, can transport larger and heavier parcels, the integrated system allows trucks to focus on heavier and larger parcels and drones on small parcels. Coordinated trucks and drones can deal with weather conditions such as snow, wind and rain, which can significantly affect drone operations. In these situations, trucks have the ability to protect them as a shelter in harsh weather. In addition, truck and drone integration can significantly optimize routing problems. A truck in conjunction with a drone can fulfill the desires of logistics companies as they can reduce the cost and time of transportation with better service.

The major advantages of drones have attracted the attention of large logistics companies. It has been almost a decade since Amazon Prime Air started working on drone delivery. In 2022, their team announced that their first drone delivery service would launch in Lockeford, California (Amazon)(Part (a) Fig. 1). Walmart stores (7 states) have front-delivery hubs operated by DroneUp, Flytrex and Zipline that have completed more than 6000 drone deliveries in less than 30 min after ordering (Walmart) (part (b) Fig. 1). Many other companies have focused on drone deliveries due to low cost and fast delivery, such as UPS (UPS), Google (Google), DHL (DHL), Uber Eats (UberEats) (part (a) Fig. 2), Workhorse (Workhorse Group) (part (b) Fig. 2) and others. The delivery van with automated loading space and autonomous drones delivery from Mercedes-Benz demonstrates the efficiency of this system in last-mile delivery (mercedes-benz) (Part (c) Fig. 2).

Recently, researchers have increasingly focused on the use of autonomous delivery drones. In 2015, Murray and Chu (2015) introduced for the first time the integration of drones with trucks, a variant of TSP where trucks and drones work together to deliver parcels to customers. Since then, the variants of truck and drone along with their challenges have been expanded in the scientific community. Several objectives have been considered, such as minimizing completion time, operating costs, energy consumption, etc.

We review and classify the existing studies with their future directions in CTD-LMD. In our study the structured literature search was applied across different academic databases, covering high-quality journal articles and conference proceedings in operations research, including Google Scholar, Web of Science and Scopus. In addition, the following keywords used in the search are "Truck and Drone delivery", "Electric Vehicle Routing Problem with Drones", "Traveling Salesman Problem with Drones", "Vehicle Routing Problem with Drone Resupply", "Flying sidekick traveling salesman problem", "Two Echelon Vehicle Routing Problem with Drones". Also, we have applied additional filters, including only English-language research papers published between 2015 and 2025(Up to March), and considered peer-reviewed journal articles, high-impact conference proceedings, and notable arXiv preprints, excluding articles not available in full text, and duplicate or outdated survey papers. The evaluation of the individual papers includes the following: 1. Clear formulation of the research objective and scope. 2. implementation of mathematical models or approaches 3. Use of benchmark data sets or the real world 4. inclusion of results and evaluations 5. Publication in a peer-reviewed publication

Articles excluded if they did not meet at least three of these five in the final analysis. The diagram Fig. 3 summarizes a PRISMA-style flow chart of the screening process, including the number of data sets identified, the steps excluded, and the final studies.

In this comprehensive literature review, we analyzed 15 literature reviews and 144 scientific papers on CTD-LMD, as Fig. 4 shows the number of papers by year. Fig. 5 shows the distribution of research articles in journals, conferences, congresses, and symposia. In addition, the abbreviations for the problem classes are listed in Appendix A Table A.1. The contributions of this paper are as follows: (i) we present a detailed overview of CTD-LMD with recent advances, (ii) we identify literature reviews on CTD-LMD by highlighting their classification and future directions, (iii) we provide a systematic research methodology to analyze the existing literature on collaborative truck and drone models, (iv) we categorize the problem based on the number of trucks and the number of drones and highlight the objectives and constraints of each category, (v) we classify the solution methods to solve CTD-LMD, (vi) we explore the challenges of this modern delivery system for future studies.

The rest of this article is structured as follows: Section 2 presents the related work of cooperation truck and drone of the literature review. Section 3 gives an overview of the classification of CTD-LMD based on the system configuration. Section 4 classifies the problem based on approaches. Section 5 summarizes the challenges and recommendations of the problem, and Section 6 concludes the review.

2. Related works

Recently, several review articles have been published on delivery by truck and drone. We summarize them in Table 1. Rojas Viloria, Solano-Charris, Muñoz-Villamizar, and Montoya-Torres (2021) investigated the different forms of routing problems with drones and their improvements. They also classified 79 studies based on their objectives, constraints, and methods (Meta-heuristics, Heuristics, and Exact algorithms) and observed a notable increase in the publication of mixed-vehicle strategies to complement routing with drones.

Chung, Sah, and Lee (2020) surveyed DO and TDCP in various sectors such as transportation/logistics, construction/infrastructure, agriculture, etc. Most of their research relates to the optimization of DO and TDCP in the context of mathematical modeling, synchronization between a drone and a truck solution, methods and constraints. Macrina, Pugliese, Guerriero, and Laporte (2020) focused mainly on delivery systems in transportation by trucks and drones. They highlighted the interest in this topic in the scientific community. In addition, they have studied various drone and truck delivery problems, primarily relying on the methodology of assumptions and characteristics. Li, Chen, Wang, and Bai (2021) reviewed publications in two echelons, specifically GV and UAV with their variants, mathematical modeling, and features.



(a) [6], [3], [2], [5]



(b) [49]



(c) [4]

Fig. 2. Evolution in delivery systems by companies.

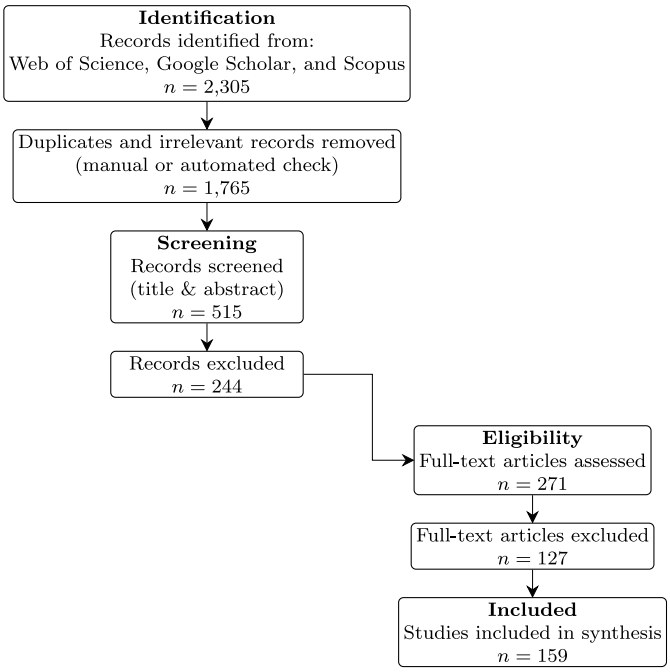


Fig. 3. PRISMA flow diagram for literature selection.

Moshref-Javadi and Winkenbach (2021) proposed an organized, comprehensive, and adaptive framework for drone-based delivery routing problems, including identifying constraints and operational planning problems in logistics models. Benarbia and Kyamakya (2021) provided a review that focuses on drone delivery systems in logistics, including some aspects such as design, modeling, performance, and approaches. Liang and Luo (2022) reviewed 60 publications on TDRP, highlighting problems, features and algorithms. Madani and Ndiaye (2022) examined 95 papers based on hybrid truck-drone delivery systems. They showed the impact of drone delivery systems by combining them with other vehicles in last-mile delivery. Another study, Li, Liu, and Jiang (2022) reviewed 36 relevant publications on drones in logistics, whose studies were based on theoretical models, application scenarios and other problems. One study, Li, Tupayachi, Sharmin, and Martinez Ferguson (2023) investigated the challenges, methods and future research aspects of drone delivery systems, focusing on analyzing their objectives, mathematical models and solution approaches. Zhang et al. (2023) mainly dealt with TDCDP and the role of trucks and drones in the delivery process. In addition, the paper studied the TDCDP models, assumptions, objectives, constraints, and solution techniques. Wang, Zheng, and Wandelt (2024) discussed the policy challenges of the coordinated delivery of trucks and drones that can help decide the regulation of technology. Dang, Liu, Luo, Liu, and Shi (2024) Categorized the problem according to various aspects such as application, modes of cooperation, vehicle configurations, objectives, constraints, and solution methods. Recent trends in dynamic routing were emphasized, alongside the identification of gaps in addressing time windows, drone limitations, and real-world constraints. The text concludes by delineating future directions that prioritize realistic models, adaptability, and sustainability. Duan, Luo, and Wang (2025) examined existing studies by categorizing them based on solution methodologies, such as exact methods, heuristic, metaheuristic, approximation, and artificial intelligence algorithms, and assessed their effectiveness on varying problem scales and complexities. In addition, the paper explores application domains, including logistics, surveillance, and emergency delivery, while considering public datasets and modeling techniques. Luo, Duan, and Wang (2025) systematically reviewed 160 studies, focusing on modeling, objectives, constraints, and solution methods for truck–drone routing problems. The paper offers a comprehensive framework to guide future research and practical applications in this field.

Our literature review is based on the classification of the problems and approaches of CTD-LMD. We also discussed the challenges of this delivery system and identified the gaps in existing work that provide directions for future studies to improve the efficiency of this complex

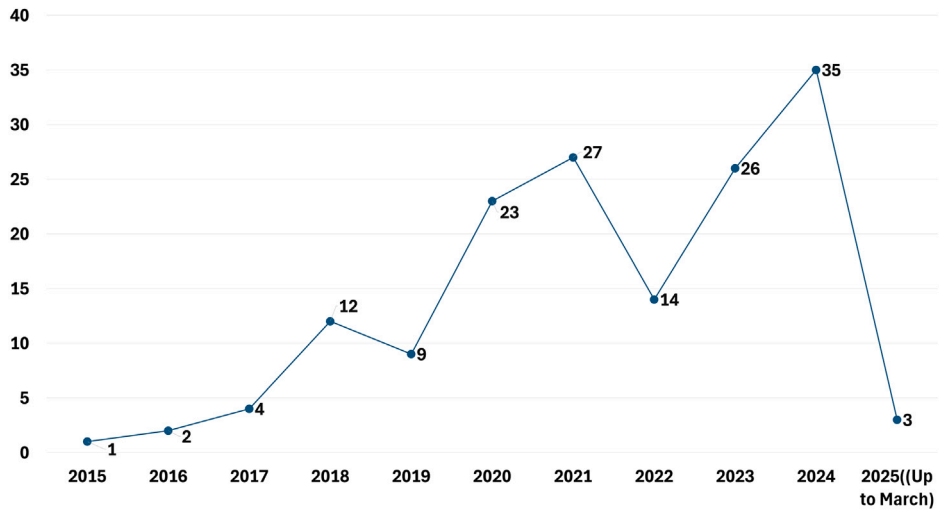


Fig. 4. Number of publications per year.

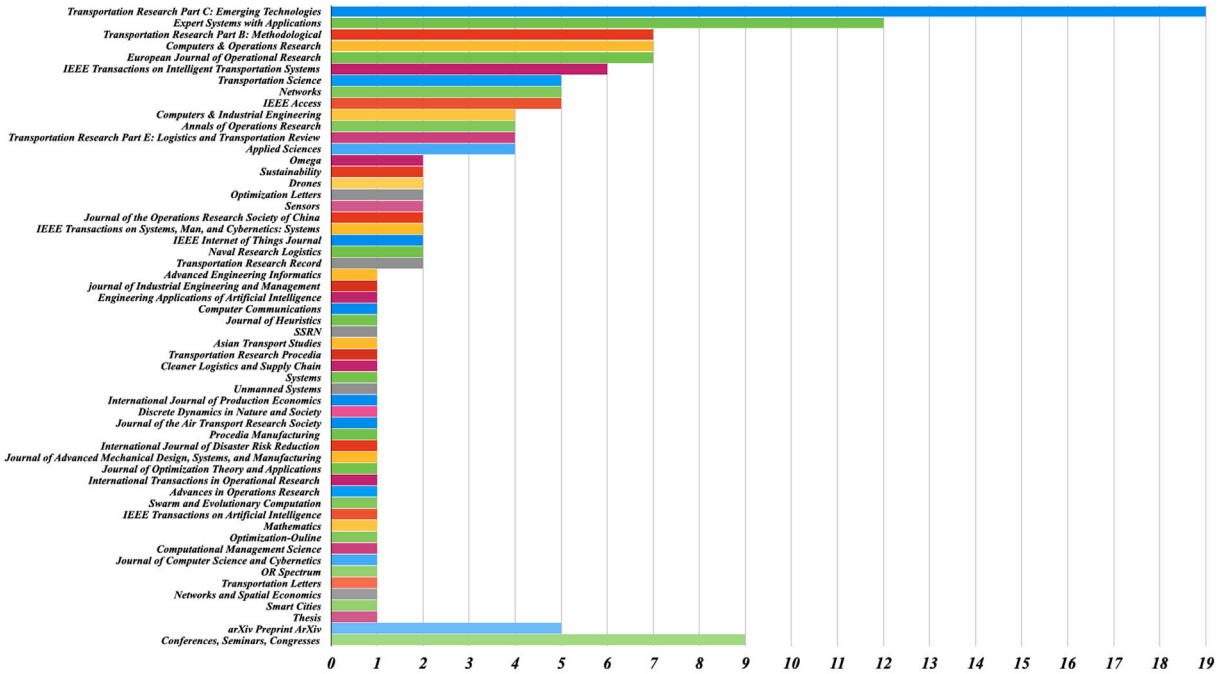


Fig. 5. Distribution of publications by outlet.

delivery problem. This study provides a comprehensive overview of a large number of studies that have emerged in recent years to address the complexity of this modern delivery system. In contrast of previous papers, this overview examines each work in the problem class (deterministic, dynamic and stochastic) and categorizes the solution approaches (exact, heuristic, metaheuristic, etc.) with an indication of the objectives and constraints of the most commonly treated approaches. The synthesis of the results of these studies also highlights the gaps and how the problem can be extended, which may be of interest for future directions. The review thus not only consolidates previous research, but also provides a roadmap for improving the scalability, realism and effectiveness of future models in this area.

3. Collaborative truck-drone delivery problems

We divided the publications into three categories based on the number of trucks and drones: Single Truck–Single Drone, Single Truck–Multiple Drones and Multiple Trucks–Multiple Drones, the publication numbers of each type are shown in Fig. 6. We have discussed the problem classes, constraints and objectives of each system separately and how this delivery system has been extended.

3.1. Single truck–single drone

The cooperation of a single truck and a single drone was first introduced by Murray and Chu (2015). They called this problem FSTSP, as shown in part (a) of Fig. 7. In their problem, there are a set of customers that need to be served exactly once by either a truck or a drone; however, some customers only need to be served by truck due to the capacity of the drone. Both truck and drone can leave the depot independently or in tandem and the drone can reconnect the truck at the customer's location or return to the depot separately. Furthermore, once the drone has taken off, the truck should drive along the road network to reconnect the drone. The objective of FSTSP is to minimize the tour completion time (the latest time at which

Table 1
Related works.

Author	Classification	Future direction	Years
Rojas Viloria et al. (2021)	Objectives Optimized, Constraints, Applications, Solution Techniques and Whether Employ an Additional Vehicle or Not	Utilizing Water Drones for Exploring Routes and Cleaning Operations, Different Optimization Problems Like Task Assignment, Unmanned Ground Vehicle Path Planning	2005 to 2019
Chung et al. (2020)	Mathematical Models, Synchronization, Solution Techniques and Hindering the Implementation of Integrated Drone-Truck Operations	Energy and Environmental Researches, Relaxing Operational Constraints, Enhancing Modeling Methods and Solution Approaches, Incorporating Uncertainty, Mixed-fleet Arc Routing Problems	Up to 2020
Macrina et al. (2020)	TSP-D, VRP-D, DDP, CVP-D	Relaxing some Assumptions, Safety, Uncertainty and Dynamic system, Realistic Drone Parameter, Energy Evaluation, Environmental Impacts	Up to 2020
Li et al. (2021)	Routing Problems of Two-Echelon within Modeling Mechanism	Mathematical Models, Improving Solution Methods, Assess the Efficiency of Models and Algorithms on Benchmark Instances	Up to 2021
Moshref-Javadi and Winkenbach (2021)	Models of Drone-Based Delivery in Logistics and Objectives, Recognizing the Gaps	Changing the Locations of Facilities and Adding Recharging Locations, Infrastructure for Launching and Receiving Drones, Space Assignment for Drones in Facilities and Trucks, Consideration of Air Traffic and Navigation Systems	Up to 2020
Benarbia and Kyamakya (2021)	Vehicle Routing Problem with Drones, Drone assignment Issue, Charging Process and Recharging Station Location, Fleet Dimensioning	Optimization in Planing: Cost, Depots Recharging Stations, Batteries, Drone Assignments and Further Research for Challenges on the Engineering Side	Up to 2021
Liang and Luo (2022)	Traveling salesman Problem with Drones and Vehicle Routing Problem with Drones, Constraints and Features, Solution Methods, Future Research Opportunities	Exact methods, Customer Requirements, Environmental Studies, Regulations of Drone Operations, Stochastic and Robust Optimization, Dynamic Orders	2015 to 2019
Madani and Ndiaye (2022)	Vehicles Roles, System Configuration, Problem Model, Solution Approaches	The Impact of Energy and Speed on the Role of a Drone, Unforeseen Circumstances like Traffic, Extreme Weather, Security, Service Time, and Changing Regulations	Up to 2022
Li, Liu, and Jiang (2022)	Theoretical Models, Various Path Planning Challenges, Application, UAV Implementation Obstacles, Costs	Weather Condition, Different methods, Dynamic Orders, the Influence of Carbon Neutrality	2021 to 2022
Li et al. (2023)	Types of the Delivery Modes in TDCDP	Considering Speed and Battery Life and Cost, Relaxing Constraints, Make Mode More Realistic	2015 to 2022
Zhang et al. (2023)	Objectives, Mathematical Models and Approaches	Multi-Objective, Dynamic Factors, Uncertainty, Complex Constraints, Large-scale Instances	Up to 2022
Wang et al. (2024)	Problem Classification, Policy Related Challenges	Airspace Safety and Security, Zone Planning and Integration, Liability and Risk Assessment, Interoperability and Standards Societal, Environment and Sustainability	Up to 2023
Dang et al. (2024)	Application Area, Problem Classification, Objectives and Constraints, Solution Methodologies	Model Construction and Algorithm Design, Adaptability to Dynamic Environments, Real-World Deployment Considerations, Environmental Sustainability	2015 to 2024
Duan, Luo, and Wang (2025)	classified Types of Solution Approaches	Model Optimization and Algorithm Design, Scalability and Efficiency, Adaptability in Dynamic Environments, Practical Applications and Real-World Deployment	2015 to 2024
Luo et al. (2025)	Vehicle Configuration, Coordination Mode, Optimization Objectives, Constraints, Solution Approach, Problem Parameters	Multi-objective and Green Optimization, Scalability and Algorithmic Efficiency, AI and Learning-based Methods, Real-world Deployment and Applications	2015 to 2024
This paper	Problem Classification, Categorization of Approaches, Challenges	Weather Condition, Traffic Conditions, Uncertain Demand, Real time Orders, Launch and Return of Drone, Heterogeneous Drone, Time windows, Pick up and Delivery, Drone's Capacity, Multiple Depots, Energy Consumption, Battery Swap/Recharging, Objectives, Cooperation Electric Truck and Drone	2015 to March 2025

either the truck or the drone returns to the depot). FSTSP was also considered by Boccia, Masone, Sforza, and Sterle (2021), Dell'Amico, Montemanni, and Novellani (2021a, 2021b), Gürel and Serdarasan (2024), Jeon et al. (2021), Ozden-Gurcan, Aksit, and Saricicek (2024), Ponza (2016), Wule, Jianhua, and Zhenhui (2020) and Mahmoudinazlou and Kwon (2023) with different solution approaches, but generally with the same objective of minimize time completion or makespan. The FSTSP problem has been extended in various ways. Gonzalez-R, Canca, Andrade-Pineda, Calle, and Leon-Blanco (2020) considered the battery lifetime of the drone in each trip, and if the charge is sufficient, the drone can make several visits (part (b) Fig. 7), assuming this energy consumption as a linear function. Another new conceptualization of FSTSP is presented by Jeon et al. (2021). Their study focused on backhaul deliveries (FSTSP-B), this model significantly improves the

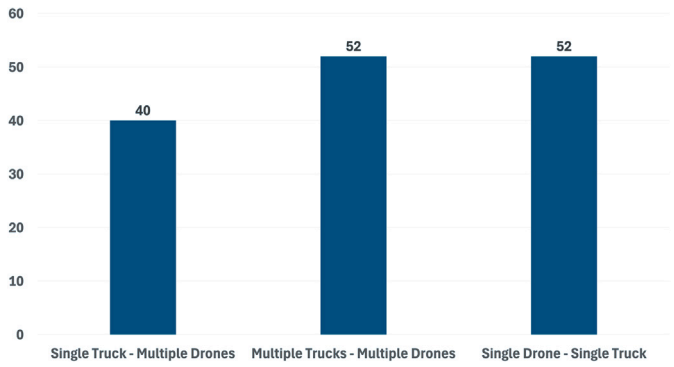


Fig. 6. Number of publications for each type.

utilization of the drone and reduces the number of empty flights. Gürel and Serdarasan (2024) investigated the problem with windy conditions, focusing on minimizing air and noise pollution to support zero pollution goals in urban environments.

Agatz, Bouman, and Schmidt (2018) introduced TSP-D with the objective of the shortest tour in time, TSP-D is very similar to FSTSP. There are some differences between them, the most important being take-off and landing. In FSTSP, drones are not allowed to land at the same take-off location, but in TSP-D this is allowed. Also, in FSTSP some customers have to be served by truck due to the heavy parcels, while in TSP-D all customers can be served either by truck or by drone. In addition, FSTSP takes into account the preparation time for lunch, recharging the battery, and loading the parcel, while TSP-D neglects them. TSP-D and its variants were investigated by AlMuhaideb et al. (2021), Baek, Chen, Chang, Macii, and Poncino (2020), Bouman, Agatz, and Schmidt (2018), Duan, Li, Zhang, Feng and and Lu (2025), Gunay-Sezer, Cakmak, and Bulkan (2023), Nguyen, Sano, and Tran (2020), Rich (2020), Roberti and Ruthmair (2021), Schermer, Moeini, and Wendt (2020), Tang and van Hoeve (2024), Tang, Hoeve, and Shaw (2019), Vásquez, Angulo, and Klapp (2021), Yurek and Ozmutlu (2018, 2021), Zhu, Boyles, and Unnikrishnan (2024b) and their objective is generally to minimize processing time. However, minimization of costs has been defined by Agatz et al. (2018), Caggiani, Marinelli, Orco, and Ottomanelli (2017), Ha, Deville, Pham, and Hà (2018, 2020), Yetis and Karakose (2021),Wang, Wang, Hu, Xue, and Guan (2022) and Zhai, Mei, Guo, and Du (2024). In addition, Yang, Yan, Cao, and Roberti (2023) focused on the objective function that maximizes profit by serving customers, Deng, Li, Ding, Zhou, and Zhang (2024) considered minimizing the risk of service delays. In one study, Caggiani et al. (2017) focused on TSP-D, where drones can take off and land not only at the customer's location but also along the route arc. In addition, Yang et al. (2023) and Duan, Li, et al. (2025) investigated a new concept of TSP-D with time windows and traffic. Capacity as a constraint was addressed in several papers, in particular Jeon et al. (2021) and Duan, Li, et al. (2025) focused on drop-off and pick-up in this model. Baek et al. (2020), Zhu, Boyles, and Unnikrishnan (2022, 2024a), Zhu et al. (2024b) investigated in an extended form of TSP-D considering electric truck and drone to make the delivery system more environmentally friendly, however, managing the energy consumption of the model makes the problem more complex. Since weather plays an important role in the delivery system, it was taken into account by Campuzano, Lalla-Ruiz, and Mes (2023). Energy consumption is another important factor studied by Baek et al. (2020), Campuzano et al. (2023), Liu, Liu, Shi, Wu, and Pedrycz (2020), Roberti and Ruthmair (2021), Zhu et al. (2022, 2024a). Multiple visits presented as a constraint by Bian, Song, He, and Chi (2024), Ha, Vu, Le, and Hoang (2021), Liu et al. (2020), Liu, Luo, Liu, Shi, and Cheng (2019), Madani, Ndiaye, and Salhi (2024), Pina-Pardo, Silva, and Smith (2021) and Duan, Li, et al. (2025).

The optimization of the delivery routes for a truck supported by a supply drone was investigated by Pina-Pardo et al. (2021) and Dienstknecht, Boysen, and Briskorn (2022) (part (c) Fig. 7). Several articles presented two-echelon concepts for this delivery process Luo, Liu, and Shi (2017) and Liu et al. (2020, 2019). In this problem, the truck starts its journey with the drone from the depot and there are some rendezvous points (part (d) Fig. 7) in the road network where the drone can be launched or landed. In a special study, Boccia, Mancuso, Masone, and Sterle (2024) has investigated two versions of the TDTLP resulting from the possibility that the drone can land or hover at the collection points. In addition, Dodge, MirHassani, and Hooshmand (2024) extended the problem and included factors such as wind speed, wind direction, drone speed and cargo weight in a comprehensive energy consumption model for drones.

The speed, endurance and flight range of drones have been considered in several papers. These factors make the problem more realistic and are crucial in delivery services as they can directly improve the quality of service, reduce operating costs and increase the efficiency of deliveries. Table 2 summarizes the concepts of collaboration between a single truck and a single drone in different classes, in terms of their constraints and objectives. Table 2 shows that different types of objectives were investigated, with the minimization of travel time and the TSP-D problem class being the most common. However, objectives related to energy consumption and customer service quality (such as minimizing risk or maximizing satisfaction) are less common. These objectives tend to be secondary or are predominantly addressed in multi-objective optimization models. The table shows the constraints such as capacity, weather, traffic, and energy consumption that reflect real drone operations. In most studies, this type of problem classification uses the customer's depot or location for the launch and return of the drone.

3.2. Single truck–multiple drones

The collaboration of a single truck and multiple drones is another delivery system that increases the efficiency of operations. Murray and Chu (2015) has introduced PDSTSP (Part (a) Fig. 8), a single truck departs directly from the depot with a fleet of drones and returns to the depot after delivering parcels. There is no synchronization between truck and drone and the objective of this problem is to minimize time. Also, Mbiadou Saleu, Deroussi, Feillet, Grangeon, and Quilliot (2018) and Dell'Amico, Montemanni, and Novellani (2020) proposed different approaches to the PDSTSP problem.

The CTD-LMD problem with single truck and multiple drones is considered by several works that mainly deal with minimizing time. However, the minimization of cost is studied by Hazama, Iima, Karuno, and Mishima (2021), Jiang, Dai, Yang, and Ma (2024), Karak and Abdelghany (2019), Salama and Srinivas (2020), Tiniç, Karasan, Kara, Campbell, and Ozel (2023) and Salama and Srinivas (2020). Also Luo et al. (2021) and Gonzalez-R, Sanchez-Wells, and Andrade-Pineda (2024) proposed Multi-Objective versions of this type of delivery system. In addition, Kyriakakis, Aronis, Marinaki, and Marinakis (2023) considered the minimization of the energy consumption of this delivery problem.

To address the limitations of the traditional delivery process, Boysen, Briskorn, Fedtke, and Schwerdfeger (2018), Karak and Abdelghany (2019), Kyriakakis et al. (2023), Moshref-Javadi, Hemmati, and Winkenbach (2020), Poikonen and Golden (2020, 2020) and Dell'Amico et al. (2020) used a truck as a mobile platform carrying unmanned aerial vehicles to reduce the number of stops required to refuel or reload the payloads carried. In addition, Hazama et al. (2021), Peng et al. (2019), Poikonen and Golden (2020) and Jeong and Lee (2023) have defined some specific locations for the take- off and landing of drones. Another method for truck stopping point and drones takeoff is clustering which is based on customer requirements proposed by Chang and Lee (2018), Lu, Kuo, Ho, and Nguyen (2022), Mourelo Ferrandez, Harbison, Webwer, Sturges, and Rich (2016), Zhang and Li (2023b),

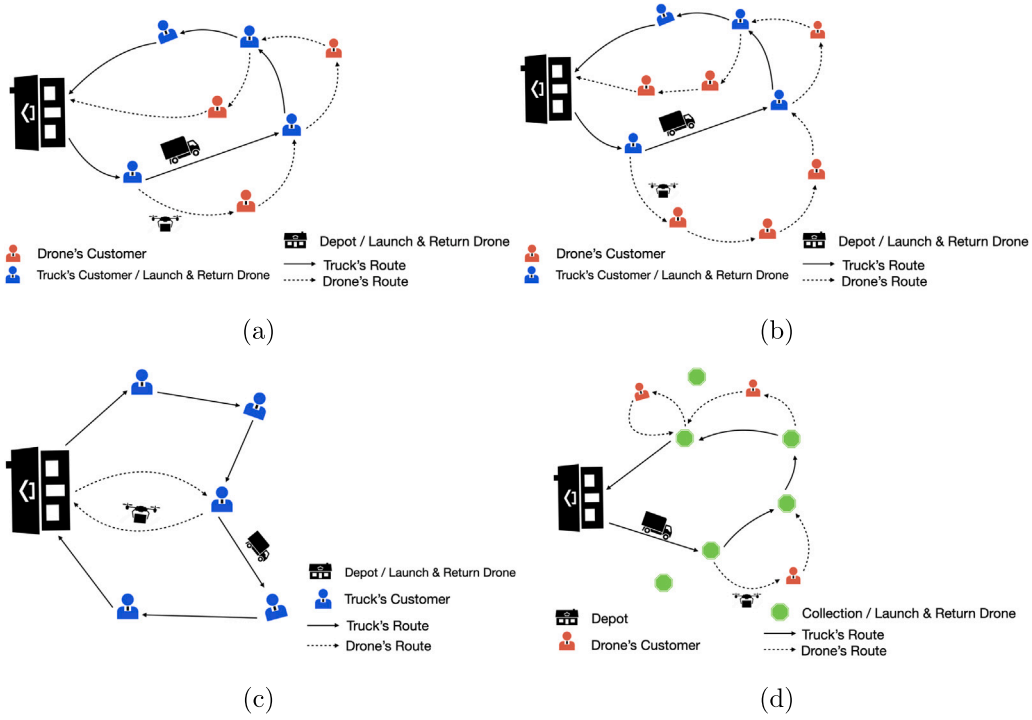


Fig. 7. Single Truck–Single Drone.

and Thomas, Srinivas, and Rajendran (2023) (Part (b) Fig. 8). For this type of delivery system, Cavani, Iori, and Roberti (2021), Delazeri and Ritt (2021), Dell'Amico et al. (2020), Gómez-Lagos, Candia-Véjar, and Encina (2021), Kang and Lee (2021), Luo, Poon, Zhang, Liu, and Lim (2021), Meng, Guo, Li, and Liu (2023), Momeni, Mirzapour Al-e Hashem, and Heidari (2023), Murray and Raj (2020), Rave (2023), Rinaldi, Primatesta, Bugaj, Rostáš, and Guglieri (2023), Salama and Srinivas (2020), Tiniç et al. (2023) and Jiang et al. (2024) considered the customer's location or depot for recharging, dispatching and loading the parcel loads onto the drones. Mishra and Tiwari (2024), on the other hand, proposed charging stations for recharging the drones battery.

Drone capacity is a key factor in the delivery process and can be affected by the drone's range, endurance, speed and battery. Drones have different payload capacities and are suitable for the transportation of smaller packages or loads. Several studies have considered this limitation to solve the delivery problem with a single truck and multiple drones in a more realistic scenario, namely from Kang and Lee (2021), Karak and Abdelghany (2019), Karaköse (2024), Kong, Jiang, Wang, Wang, and Song (2023), Kyriakakis et al. (2023), Luo, Poon, et al. (2021), Meng et al. (2023), Momeni et al. (2023), Murray and Raj (2020), Thomas et al. (2023), Zhang and Li (2023b), Zhao et al. (2022) and Pina-Pardo, Silva, Smith, and Gatica (2024a). Drop-off and pick-up is also a challenge in the routing problem that Jiang et al. (2024), Karak and Abdelghany (2019), Meng et al. (2023) and Zhang and Li (2023b) tackle to solve this delivery system. Kang and Lee (2021), Murray and Raj (2020), Yılmaz, Cengiz, and Kahraman (2024), Zhao et al. (2022) and Thomas et al. (2023) heterogeneously incorporated that drones with different payload capacity can pick up packages with different weight, this diversity brings challenges in solving this delivery system problem.

To make the delivery problem more effective, the drone can be allowed to perform a single flight while visiting multiple locations (Part (c) Fig. 8). This scenario requires efficient routing to find the optimal stops. Several works have considered this constraint, Delazeri and Ritt (2021), Gonzalez-R et al. (2024), Karak and Abdelghany (2019), Luo, Poon, et al. (2021), Meng et al. (2023), Momeni et al. (2023), Murray and Raj (2020), Peng et al. (2019), Poikonen and Golden (2020), Zhang and Li (2023b) and Jiang et al. (2024). The drone's energy consumption is another major challenge in this delivery process system. The management of energy consumption is a crucial facet for a successful implementation, which Mirzapour Al-e Hashem, Hejazi, Haghverdizadeh, and Shidpour (2024), Kong et al. (2023), Kyriakakis et al. (2023), Luo, Poon, et al. (2021), Mourelo Ferrandez et al. (2016), Poikonen and Golden (2020), She and Ouyang (2024) and Momeni et al. (2023) to solve this complex problem (Part (d) 8). The time window in which the vehicle must arrive at the customer's location as a constraint was extended by Kong et al. (2023). In addition, the effects of electric trucks and weather conditions were analyzed in detail by Mirzapour Al-e Hashem et al. (2024). She and Ouyang (2024) proposed an extended form of this problem that includes airspace congestion from a large number of drones.

We have listed all the types of collaboration between a truck and multiple drones along with their constraints and objectives in Table 3. As reflected in the table, time and cost minimization are the most commonly adopted objectives, and constraints related to vehicle capacity, vehicle drop and pick-up, and multiple visits form the backbone of most routing models. However, more specific constraints such as energy consumption, traffic, weather, heterogeneous and electric trucks appear in a smaller subset of the table. Emerging focus areas to different locations for departure and return have also received moderate attention in this problem class.

3.3. Multiple trucks–multiple drones

The collaboration of multiple trucks and multiple drones is an extended form of the truck and drone delivery system which increases the complexity of this modern delivery problem, as illustrated in Fig. 9. This problem has received attention in the literature from researchers with various objectives. Most work has focused on minimizing time and cost, as reducing them can increase operational effectiveness and profitability. However, maximizing orders is an essential objective to improve the efficiency of delivery systems with multiple trucks

Table 2
Single truck–Single drone.

Author	Problem class	Min time	Min cost	Max order	Multi obj	Min energy consumption	Min risk	Drone lunch and return	Time windows	Capacity	Drop/Pick up	Multi visit	Energy consumption	Electric truck	Weather	Traffic
Murray and Chu (2015)	FSTSP	✓						D/C								
Agatz et al. (2018)	TSP-D	✓						D/C								
Ponza (2016)	FSTSP	✓						D/C								
Luo et al. (2017)	2E-GU-RP	✓						PL								
Caggiani et al. (2017)	TSP-D		✓					Arc								
Ha et al. (2018)	TSP-D		✓					D/C								
Yurek and Ozmutlu (2018)	TSP-D	✓						D/C								
Bouman et al. (2018)	TSP-D	✓						D/C								
Ha et al. (2020)	TSP-D		✓					D/C								
Liu et al. (2019)	2E-GUCRP	✓						PL				✓				
Tang et al. (2019)	TSP-D	✓						D/C								
Dell'Amico et al. (2021a)	FSTSP	✓						D/C								
Dell'Amico et al. (2021b)	FSTSP	✓						D/C								
Liu et al. (2020)	2E-RP-TD		✓					D/C		✓		✓	✓			
Rich (2020)	TSP-D	✓						D/C								
Gonzalez-R et al. (2020)	TDTL	✓						D/C				✓	✓			
Schermer et al. (2020)	TSP-D	✓						D/C								
Roberti and Ruthmair (2021)	TSP-D	✓						D/C					✓			
Baek et al. (2020)	TSP-D	✓						D/C		✓			✓	✓		
Nguyen et al. (2020)	TSP-D	✓						D/C								
Wule et al. (2020)	HCVTSP	✓						D/C								
Boccia et al. (2021)	FSTSP	✓						D/C		✓						
Yu, Lin, Jodiawan, and Lai (2023)	FSTSP	✓						D/C		✓						
Ha et al. (2021)	TSP-MVD	✓						D/C		✓		✓				
Vásquez et al. (2021)	TSP-D	✓						D/C								
Yetis and Karakose (2021)	TSP-D		✓					D/C								
Pina-Pardo et al. (2021)	TSPRD- DR	✓						D/C		✓		✓				
Jeon et al. (2021)	FSTSP-B	✓						D/C			✓					
Wu, Fan, Shi, and Feng (2021)	TDCDP	✓						D/C		✓						
AlMuhaideb et al. (2021)	TSP-D	✓						D/C								
Yurek and Ozmutlu (2021)	TSP-D	✓						D/C								
Yang et al. (2023)	TSP-D			✓				D/C	✓							✓
Wang et al. (2022)	TDHRP-TDRTT		✓					C		✓						✓
Zhu et al. (2022)	EVTSPD-FF		✓					C		✓			✓	✓		
Campuzano et al. (2023)	ATSP-D,VS-ATSP-D	✓						D/C		✓			✓		✓	
Mahmoudinazlou and Kwon (2023)	TSP-D, FSTSP	✓						D/C								
Gunay-Sezer et al. (2023)	TSP-D	✓						D/C								
Ndiaye, Osman, Salhi, and Madani (2023)	TDRP	✓						D/C								
Madani et al. (2024)	HTD- MVMLR		✓					C/S		✓		✓				
Zhang, Campbell, and Sweeney II (2024)	TD		✓					D/C		✓						
Zhu et al. (2024a)	BEVTSPD					✓		D/C		✓			✓	✓		
Bian et al. (2024)	DHDR		✓					Sa		✓		✓				
Zhai et al. (2024)	TSP-D		✓					D/C								
Dienstknecht et al. (2022)	TSP-DR		✓					D/C								
Boccia et al. (2024)	TDTLP	✓						S		✓						
Deng et al. (2024)	TDRP						✓	C	✓	✓						
Dodge et al. (2024)	DTCO				✓			C		✓		✓	✓		✓	
Ozden-Gurcan et al. (2024)	FSTSP				✓			D/C		✓			✓			
Tang and van Hoeve (2024)	TSP-D		✓					D/C								
Duan, Li, et al. (2025)	TMCRP-PD				✓			D/C	✓	✓	✓	✓				✓
Zhu et al. (2024b)	PHEVTSPD	✓						D/C		✓			✓	✓		
Gürel and Serdarasan (2024)	FSTSP	✓						D/C					✓		✓	

D/C: Depot or Customer's Location, PL: Parking Lots, C: Truck's Customers, Site/Station: S, Satellite: Sa

and drones, which Ulmer and Thomas (2018) and Dayarian, Savelsbergh, and Clarke (2020) have considered. The Multi-objective variants for this delivery system was explored by Das, Sewani, Wang, and Tiwari (2020), Khalaj Rahimi and Rahmani (2024), Zhang and Li (2023a) and Kuo, Edbert, Zulvia, and Lu (2023). This aims to identify well-rounded solutions that address the different aspect of efficient delivery. Kyriakakis, Stamadianos, Marinaki, and Marinakis (2022) is the only study that aims to minimize energy consumption. It focuses on the optimization of routes and processes to reduce the energy consumption of vehicles

The take-off and landing drone for this delivery system was considered in various locations. Deng, Amirjamshidi, and Roorda (2020), Ham (2018), Sawadsitang, Niyato, Tan, and Wang (2018), Ulmer and Thomas (2018), Wang and Sheu (2019), and Ghiasvand, Rahmani, and Moshref-Javadi (2024) considered a multi-trucks and drone deliveries distribution center, which is a central location where drones and

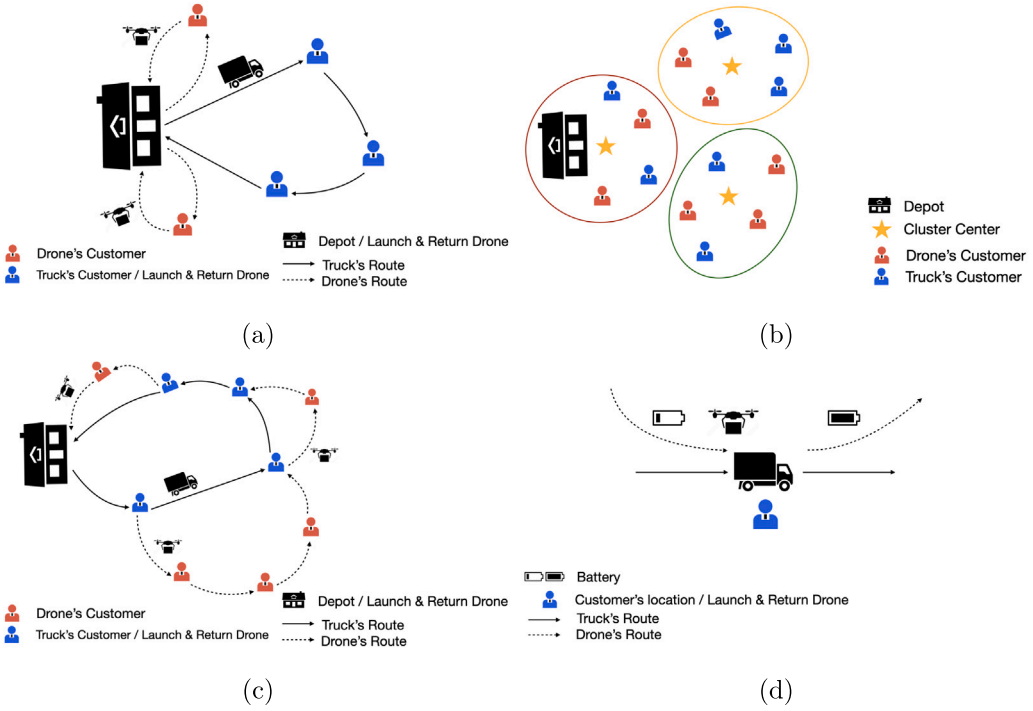


Fig. 8. Single Truck–Multiple Drones.

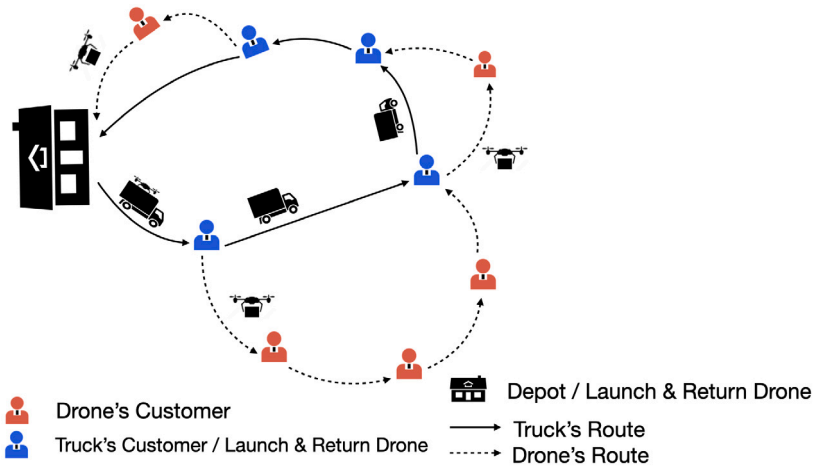


Fig. 9. Multiple Trucks–Multiple Drones.

trucks can load packages and deploy them for deliveries after serving customers and returning to the depot. So, Bakir and Tiniç (2020), Cui and Lei (2021), Daknama and Kraus (2017), Dayarian et al. (2020), Di Puglia Pugliese, Guerriero, and Scutellá (2021), Dukkanci, Kara, and Bektaş (2021), Kitjacharoenchai et al. (2019), Kuo et al. (2023), Kuo, Lu, Lai, and Mara (2022), Liu, Han, Zhang, Li, Jiang, et al. (2023), Liu et al. (2024), Luo, Gu, Poon, Liu, and Lim (2022), Mara, Sarker, Essam, and Elsayed (2023), Ren, Fan, Bao, and Fan (2023), Schermer, Moeini, and Wendt (2018, 2019b), Tamke and Buscher (2021), Wang, Poikonen, and Golden (2017), Yin et al. (2023),Bogyrbayeva, Dauletbayev, and Meraliyev (2025), Kong and Jiang (2024), Mara, Sarker, Essam, and Elsayed (2024), Zhou, Yu, Xue, and Yang (2025) and Sacramento, Pisinger, and Ropke (2019) dealt with the depot and customer's location for the loading, take-off and landing of the drones. Also Kitjacharoenchai, Min, and Lee (2020), Kong and Jiang (2024), Meng, Li, Liu and Chen (2024), Pugliese, Guerriero, and Macrina (2020), Wei, Fan, Ren, and Diao (2025) and Das et al. (2020) only considered the customer's location for the take-off and landing of the drones. Numerous studies looked at the use of trucks or vans as a means of transportation for the drones to charge the batteries, for dispatching and for loading the packages onto the drones for delivery. Di Puglia Pugliese et al. (2021), Li, Wang, Chen, and Bai (2020), Schermer, Moeini, and Wendt (2019a) and Zhang and Li (2023a) investigated this problem with clusters, i.e. a distribution point and the location where the parcels are handed over by drones. Moreover, Li, Chen, Wang and Zhao (2022) utilized the arc (between the nodes) and Faiz, Vogiatzis, et al. (2020), Kyriakakis et al. (2022), Moshref-Javadi, Van Cauwenberghe, McCunney, and Hemmati (2023) and Khalaj Rahimi and Rahmani (2024) defined some special locations for drone takeoff and landing.

In a realistic scenario, capacity as a constraint in delivery systems with multiple trucks and drones affects the limits of drone delivery and requires competent management. Although it is a more complicated problem, this constraint has been studied in several papers, it is shown in Table 4. Moreover, the capacity of each drone may vary, so Ulmer and Thomas (2018) and Li, Ignatius, Wang, Yin, and

Table 3
Single truck–Multiple drones.

Author	Problem class	Min time	Min cost	Max order	Multi obj	Min energy consumption	Drone lunch and return	Time windows	Capacity	Drop/Pick up	Heterogeneous	Multi visit	Electric truck	Weather	Traffic	Energy consumption
Murray and Chu (2015)	PDSTSP	✓					D									
Mourelo Ferrandez et al. (2016)	TSP-D	✓					CL									✓
Chang and Lee (2018)	TSP-D	✓					CL									
Mbiadou Saleu et al. (2018)	PDSTSP	✓					D									
Boysen et al. (2018)	TSP-D	✓					C									
Karak and Abdelghany (2019)	HVDRP		✓				S		✓	✓		✓				
Hu et al. (2018)	VURA	✓					A									
Peng et al. (2019)	TSP-D	✓					A					✓				
Poikonen and Golden (2020)	K-MVDRP	✓					D/C					✓				✓
Moshref-Javadi et al. (2020)	STRPD	✓					D/C									
Murray and Raj (2020)	mFSTSP	✓					D/C		✓		✓	✓				
Salama and Srinivas (2020)	TSP-D		✓				D/C									
Dell'Amico et al. (2020)	PDSTSP	✓					D									
Gómez-Lagos et al. (2021)	TSPDP	✓					PL									
Delazeri and Ritt (2021)	TSP- MFS	✓					D/C					✓				
Luo, Poon, et al. (2021)	MTSP-MD	✓					D/C		✓			✓				✓
Cavani et al. (2021)	TSP-MD	✓					D/C									
Kang and Lee (2021)	HDTRP	✓					C		✓							
Hazama et al. (2021)	TSP-D	✓					T									
Luo et al. (2021)	Mo- CRPTW-mD				✓		D/C									
Wu, Zhao, Cheng, and Ma (2022)	VD-ARP	✓					Arc									
Lu et al. (2022)	FSTSP	✓					CL									
Zhao et al. (2022)	RTSP-mD	✓					C		✓		✓					
Tiniç et al. (2023)	TSP-D		✓				D/C									
Meng et al. (2023)	MDRP-PD		✓				D/C		✓	✓		✓				
Zhang and Li (2023b)	MDVRPSPD		✓				CL		✓	✓		✓				
Rave (2023)	TSPmD	✓					D/C									
Momeni et al. (2023)	VRP-D	✓					D/C		✓			✓				✓
Rinaldi et al. (2023)	mFSTSP	✓					D/C									
Kyriakakis et al. (2023)	EM-DRP-PD					✓	Sa		✓	✓						✓
Jiang et al. (2024)	MFS-VRPD		✓				D/C			✓		✓				
Thomas et al. (2023)	CTDRSP-ELR	✓					CL		✓		✓	✓				
Jeong and Lee (2023)	DRP-T	✓					L									
Gonzalez-R et al. (2024)	TmDTL				✓		D/C					✓				
Karaköse (2024)	HTMDP	✓					C		✓							
Kong et al. (2023)	VRP-D	✓					D/C	✓	✓			✓				✓

(*continued on next page*)

Cheng (2024) considered heterogeneous for cooperation between multiple trucks and multiple drones delivery problems. However, for this complicated delivery problem, drop and pick up is proposed by Ham (2018), Khalaj Rahimi and Rahmani (2024), Li et al. (2024), Liu et al. (2023), Luo et al. (2022), Meng, Chen, and Li (2024) and Mulumba and Diabat (2024). Service demand in a time window is a critical factor for customer expectation that coordination of vehicle movements brings difficulties in route optimization, which is studied by Deng et al. (2020), Ham (2018), Kong and Jiang (2024), Kuo et al. (2023, 2022), Li, Chen, et al. (2022), Li et al. (2020), Liu et al. (2024), Meng, Chen, and Li (2024), Meng, Li, et al. (2024), Pugliese et al. (2020), Wei et al. (2025), Yin et al. (2023), Zhang and Li (2023a), and Li et al. (2024).

Ham (2018), Li, Chen, et al. (2022), Li et al. (2024), Liu et al. (2023), Meng, Chen, and Li (2024), Moshref-Javadi et al. (2023), Wang

Table 3 (*continued*).

Author	Problem class	Min time	Min cost	Max order	Multi obj	Min energy consumption	Drone lunch and return	Time windows	Capacity	Drop/Pick up	Heterogeneous	Multi visit	Electric truck	Weather	Traffic	Energy consumption
Pina-Pardo et al. (2024a)	DTSP-DR			✓			D/C		✓			✓				
Mirzapour Al-e Hashem et al. (2024)	TSP-D	✓					S						✓	✓		✓
Mishra and Tiwari (2024)	TSP-D		✓				S		✓			✓				
She and Ouyang (2024)	TDRP		✓				M								✓	
Yılmaz et al. (2024)	TSP-D	✓					D/C		✓							

Depot: D, D/C: Depot or Customer's Location, C: Truck's Customers, Anchor:A, Parking Lots:PL, Take Off:T Cluster: CL, Launch Location: L, Site/Station: S, Mobile: M

and Sheu (2019),Kong and Jiang (2024), Li et al. (2020), Meng, Li, et al. (2024), Mulumba and Diabat (2024), Pina-Pardo, Silva, Smith, and Gatica (2024b), Ren et al. (2023) and Ghiasvand et al. (2024) investigated multiple visits as a constraint which poses a challenge in route optimization. Another unique challenge is the monitoring of energy consumption, which is crucial for drone operations, which was recently studied by Di Puglia Pugliese et al. (2021), Dukkanci et al. (2021), Kong and Jiang (2024), Kuo et al. (2023), Kyriakakis et al. (2022), Li et al. (2024), Liu et al. (2024), Mara et al. (2023), Meng, Chen, and Li (2024), Momeni, Soleimani, Shahparvari, and Afshar-Nadjafi (2022), Tamke and Buscher (2021), Wei et al. (2025), Zhou, Qin, Cheng, and Rousseau (2023) and Ren et al. (2023). Traffic conditions are a notable factor in the delivery system presented by Imran and Won (2024), Wei et al. (2025) and Zhou et al. (2025). Compliance with regulations and allowed flight zones is an important constraint for drone operations that has been studied by Liu et al. (2023), Wei et al. (2025) and Zhou et al. (2025). To reduce the impact on the environment, Kong and Jiang (2024), Kyriakakis et al. (2022), Mara et al. (2023, 2024) and Ren et al. (2023) have introduced the collaboration of multi-electric trucks and multi-drones to increase the efficiency of this routing problem.

As shown in Table 4, the objectives and constraints in the development of multi-trucks and multi-drone collaboration in delivery, these concepts have been explored. The most frequently encountered objective function is the minimization cost and in constraint-wise, the vehicle capacity, energy consumption and multi visit constraint appear in most studies, that serving as a fundamental rules to ensure feasible load distribution. This class of problem has been considered with different locations for take-off and return drones, which is a significant improvement in this type of modern delivery problem.

In CTD-LMD, the number of trucks and drones plays an important role in the solution method, complexity and efficiency. In the early research of CTD-LMD, the model with a single truck and a single drone is the simplest configuration that has been used in many researches, but it is limited due to the practical scalability. A more advanced model is a single truck and multiple drones. Coordinating a single truck with multiple drones makes this delivery system more complicated, but significantly shortens the delivery time. Finally, multiple trucks and multiple drones is the most challenging configuration where the entire fleet needs to be optimized together. However, this requires advanced modeling and solution methods. In summary, as the number of trucks and drones increases, the system becomes more efficient, but also more complex in its modeling, computation and solution approaches, especially when the instances are large and the constraints are more realistic.

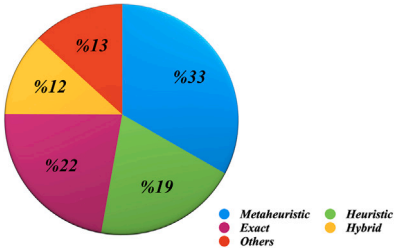


Fig. 10. Methods.

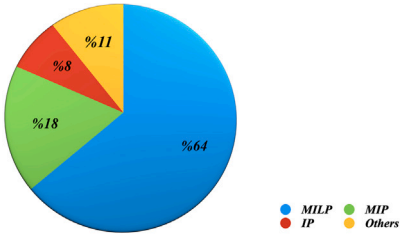


Fig. 11. Modeling techniques.

4. Approaches

Several solutions to this complex problem have been presented, classified as Exact, Heuristic, Meta-heuristic, Hybrid Meta-heuristic and others. Fig. 10 illustrates the percentage of use of each method and Fig. 11 shows the percentage of modeling techniques in collaborative Truck and drone delivery problems. In addition, by analyzing the papers, we found that Cplex and Gurobi are the most commonly used solvers, and the programming language percentages show in Fig. 12 that Python and C++ are the most commonly used programming languages.

4.1. Exact methods

Exact methods achieve the best solution according to the objective definition. They are designed to find the best solution in the solution space. Branch and Cut (B&C) is a common exact algorithm often used for combinatorial optimization. Some studies have considered this approach to find the optimal solution for CTD-LMD, despite the challenges involved, especially for larger instances.

Table 4
Multiple trucks–Multiple drones.

Author	Problem class	Min time	Min cost	Max order	Multi obj	Energy consumption	Drone lunch and return	Time windows	Capacity	Drop/Pick up	Heterogeneous	Multi visit	Electric truck	Weather	Traffic	Energy consumption
Wang et al. (2017)	VRP-D	✓					D/C									
Daknama and Kraus (2017)	VRP-D	✓					D/C									
Schermer et al. (2018)	VRP-D	✓					D/C									
Ham (2018)	PDSTSP	✓					D	✓		✓		✓				
Ulmer and Thomas (2018)	VRP-D			✓			D		✓		✓					
Sawadsitang et al. (2018)	GADOP		✓				D		✓					✓		
Deng et al. (2020)	VRPMS		✓				D/C	✓	✓							
Kitjacharoenchai et al. (2019)	mTSP	✓					D/C		✓							
Schermer et al. (2019a)	VRP-D	✓					Arc									
Wang and Sheu (2019)	VRP-D		✓				H					✓				
Schermer et al. (2019b)	VRP-D	✓					D/C									
Kitjacharoenchai et al. (2020)	2EVRPD	✓					C		✓							
Dayarian et al. (2020)	VRPDR			✓			D/C		✓							
Faiz et al. (2020)	2EVRP-HD-UAV		✓				H									
Bakir and Tiniç (2020)	VRPFD	✓					D/C									
Li et al. (2020)	2E-VRP-TM		✓				Sa	✓	✓			✓				
Tamke and Buscher (2021)	VRP-D	✓					D/C									✓
Sacramento et al. (2019)	VRP-D		✓				D/C		✓							
Pugliese et al. (2020)	VRP-D		✓				C	✓	✓							
Cui and Lei (2021)	VRP-D		✓				C/D									
Dukkanci et al. (2021)	ERDDP		✓				C/D									✓
Di Puglia Pugliese et al. (2021)	VRP-DTW		✓				D/C									✓
Das et al. (2020)	VRP-D				✓		C									
Momeni et al. (2022)	VRP-D		✓				D/C									✓
Li, Chen, et al. (2022)	TDRP-SA	✓					Arc	✓	✓			✓				
Kyriakakis et al. (2022)	EVRPD					✓	DC		✓				✓			✓
Zhang and Li (2023a)	CVDDN				✓		CL	✓								
Luo et al. (2022)	OPDP-MTMV		✓				D/C		✓	✓						
Kuo et al. (2022)	VRPTWD		✓				D/C	✓	✓							
Zhou et al. (2023)	2E-VRP-D	✓					Sa		✓							✓
Yin et al. (2023)	TD-DRPTW		✓				D/C	✓	✓			✓				
Kuo et al. (2023)	VRP-D				✓		D/C	✓								✓
Moshref-Javadi et al. (2023)	DRMTP	✓					TP		✓			✓				
Mara et al. (2023)	EVDRP	✓					D/C		✓				✓			✓
Liu et al. (2023)	MDVRPSP DNF		✓				D/C		✓	✓		✓				
Ren et al. (2023)	TDEVRP-D- SMBS		✓				D/C		✓			✓	✓			✓
Ghiasvand et al. (2024)	MTDRP	✓					DC					✓				
Meng, Chen, and Li (2024)	mDPD-T		✓				S	✓	✓	✓		✓				✓
Pina-Pardo et al. (2024b)	VRPRD-DR	✓					DC		✓			✓				
Li et al. (2024)	VRPSDP-TDH		✓				C	✓	✓	✓	✓	✓				✓
Khalaj Rahimi and Rahmani (2024)	MHTDRP-PD-R				✓		LD			✓						
Mulumba and Diabat (2024)	DAPDP		✓				D/C		✓	✓		✓				
Imran and Won (2024)	VRPD-DT		✓				D/C		✓							
Liu, Liu, and Qi (2024)	DADR				✓		D		✓						✓	
Kong and Jiang (2024)	C-TDRP		✓				C	✓	✓			✓				✓
Zhao, Long, Xie, Xu, and Liu (2025)	DTDC	✓					M									
Mara et al. (2024)	EVDRP		✓				D/C						✓			✓
Meng, Li, et al. (2024)	VRP-D		✓				C	✓	✓			✓				
Liu et al. (2024)	VRPTW-MD		✓				D/C	✓	✓							✓
Bogyrbayeva et al. (2025)	VRP-D	✓					D/C									
Zhou et al. (2025)	VRP-D	✓					D/C					✓			✓	
Wei et al. (2025)	TDVRPD-VRZ-NFZ		✓				C	✓							✓	✓

Depot: D, D/C: Depot or Customer's Location, Parking Lots: PL, C: Truck's Customers, Mobile: M, Distributions Center: DC, Hotspot: H, Cluster: CL, Transshipment Points: TP, Local Depots: LD, Site/Station: S, Satellite: Sa

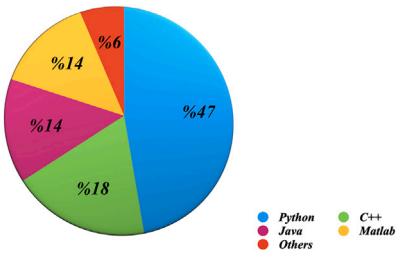


Fig. 12. Programming languages.

Schermer et al. (2020) first proposed an MILP model for TSP-D with an implementation of the B&C algorithm to find an optimal solution for instances with up to 20 customers, and Dell'Amico et al. (2021a) presented three-indexed and two-indexed MILP models for FSTSP that can be implemented in a B&C algorithm. However, this algorithm was considered for application and further development. Tamke and Buscher (2021) focused on this approach to solve the VRPD problem. They were able to use the B&C algorithm for the MILP model and showed the effect of different combinations of valid inequalities. They found optimal solutions for unbounded drone ranges with up to 20

customers and with bounded drone ranges up to 30 customers. Furthermore, Boccia et al. (2021) combined Branch and Cut algorithm with a Column Generation method for the FSTSP problem and showed that the best results are obtained for multiple instances with up to 19 customers and some instances with 20 customers. Cavani et al. (2021) proposed an exact decomposition method based on the B&C algorithm with a MILP model for TSPD. Their method is able to achieve the best solution for instances with up to 24 customers. Tiniç et al. (2023) provided a B&C algorithm to optimally solve the TSP with multiple drones, and they showed that this method outperforms using a flow-based model. In addition, Yin et al. (2023) developed a Branch and Price and Cut algorithm that efficiently solved the truck-based drone delivery routing problem with time windows. To improve the performance of the algorithm, they incorporated subset inequalities to tighten the lower bound and solved the instances with 40 customers.

Branch and Price (B&P) is another important exact algorithm that has been studied for cooperative truck and drone delivery. Wang and Sheu (2019) proposed a MIP model for VRPD and developed a B&P algorithm. For the price subproblem, they created a special network capable of determining different types of paths and nodes, and improved the pulse algorithm within pruning and expansion strategies. They evaluate the alternative Lagrangian lower bound and implant the Column Generation Stabilization, which can find the optimal solution for instances with 10 and 15 nodes in 2 h on average, in their analysis, this solution can save 20% of the cost on average and the delivery time for the customer is 5 min on average. Roberti and Ruthmair (2021) presented a B&P approach for TSP-D based on the recursion of dynamic programming and based on a set partitioning model using ng-route relaxation(a technique used in the pricing problem) and three-level hierarchical branching. Its method works efficiently and is able to find an optimal solution for instances with up to 39 customers. Yang et al. (2023) has dealt with RDTDP. They have considered the uncertainty in road traffic and their proposed B&P approach works effectively and is able to solve instances with up to 40 customers. The feasibility ratio in their robust solution is 90% higher than the deterministic solution. Zhou et al. (2023) presented a B&P algorithm for 2E-VRP-D and first applied a tabu search algorithm to speed up the algorithm, they found the best solutions for instances with up to 35 customers. Li et al. (2024) demonstrated that the B&P&C algorithm has high performance compared to traditional methods, especially for large instances. Zhu et al. (2024a) used B&P to solve BEVTSPD, their algorithm uses a dynamic programming method to identify the most cost-effective routes for column generation based on the ng-route relaxation of the problem. For TSP-D, Tang and van Hoeve (2024) applied an iterative algorithm to compute dual bounds motivated by connections between Decision Diagrams (DDs) and dynamic programming (DP) models used for pricing in branch-and-cut-and-price algorithms. The results show that dual bounds are effective for solving larger problem instances.

The Benders Decomposition (BD) algorithm as an exact approach has been studied in some works for cooperative trucks and drones. Kang and Lee (2021) applied this algorithm to HDTRP by proposing a custom banders cut and preprocessing steps that include primary heuristics and variable constraints. Vásquez et al. (2021) proposed a Two-Stage mathematical MIP model and applied a BD algorithm to find an optimal solution to the TSP-D problem, their algorithm works efficiently on various computationally simulated experiments and was developed with two sets of valid inequalities. Di Puglia Pugliese et al. (2021) presented a BD algorithm for trucks and drones under the uncertain energy consumption problem, the algorithm effectively solves the benchmark instances with extended energy consumption. Momeni et al. (2022) introduced BD for the VRPD problem and achieved significant results for large problem instances with 90 clients, demonstrating the effectiveness of this algorithm. Sawadsitang et al. (2018) presented an L-shape decomposition method for GADOP to reduce the computation time for finding the optimal solution of stochastic version of the problem.

Constraint Programming (CP) was used to solve combinatorial problems and focuses on the relationships between variables and constraints. Ham (2018) introduced two CP for a problem that is clearly modeled as an unconnected PDSTSP with drop and pick up. In addition, Tang et al. (2019) introduced a CP model for a TSP-D problem, showing that the CP model is remarkably fast and can solve instances with up to 60 customers.

Bouman et al. (2018) provided the first dynamic programming model for the TSP-D problem and they showed that their approach is capable of solving larger problems than mathematical programming approaches and they showed that limiting the number of operations can reduce the solution time.

Dell'Amico et al. (2021b), Gürel and Serdarasan (2024), Ozden-Gurcan et al. (2024), Pugliese et al. (2020) and Rave (2023) have proposed mathematical model for cooperative truck and drone delivery problems. They found optimal solutions for mostly small instances by using commercial optimization solvers such as Cplex and Gurobi. In addition, Dell'Amico et al. (2021b) presented a two-indexed mathematical programming model for FSTSP, which is able to solve 59 of the 72 benchmark instances (Murray & Chu, 2015) with an average percentage gap between the best lower and upper bound of 1.70% in a short computation time. Rave (2023) presented an effective two-indexed MILP model for the TSPmD problem, which solved the instances with up to 28 customers for benchmark instances and with a performance of saving makespan with an average of 2.7%. Dukkanci et al. (2021) presented a nonlinear model and formulated it as a Second Order Cone Programming method to solve ERDDP with the goal of energy minimization. Mishra and Tiwari (2024) designed an exact Hungarian algorithm (for the assignment of trucks and drones) under the defined constraints to find optimal solutions. Dodge et al. (2024) proposed a Progressive Hedging Algorithm (PHA) to deal with the complexity caused by the stochastic nature of wind conditions. They proposed a MINLP model and reformulated it to a MILP with linear approximations. The approach is investigated on different instances to demonstrate its efficiency in solving the problem.

Table 5 summarizes all studies that focus on exact methods. It shows the exact types of optimization methods, the type of mathematical formulations (such as MILP, IP, MINLP), the modeling framework (deterministic, stochastic or dynamic), the number of clients and the computational tools used (programming languages and solvers). From the collected data, deterministic MILP formulations with branch and cut or branch and price are the most commonly used method, especially for small to medium sized problem instances. Most instances are randomly generated with a number of 10 to 100, depending on the scalability of the method.

4.2. Heuristic methods

Heuristic algorithms were used to solve CTD-LMD. First, for FSTSP, Murray and Chu (2015) proposed heuristic route and reassign algorithms based on Savings, Nearest Neighbor and Sweep, and for PDTSP, they applied the mechanism of Savings and Nearest Neighbor to find a solution for up to 20 customers, and they emphasized the efficiency of the heuristic algorithms on larger instances that commercial solvers cannot solve. HCVTSP was solved by Wule et al. (2020). They applied a Heuristic Local Algorithm to the MILP model of this problem and compared the solutions of HCVTSP with FSTSP and achieved a significant improvement in mission time. Moreover, Jeon et al. (2021) solved the FSTSP considering the backhaul and used a heuristic Adjacent Distance-based Assignment (ADA) algorithm to solve instances with up to 100 customers in a short computation time. Murray and Raj (2020) introduced a MILP model for the mFSTSP problem and solved a Three-Phase heuristic algorithm that first constructs the initial solution within a clustering mechanism and then optimizes the problem by reordering the assignment of drones, demonstrating the ability to solve large instances where time saving is important when the problem involves

Table 5
Exact methods.

Author	Mathematical model	Method	Deterministic	Dynamic	Stochastic	Number of customers	Solver	Programming language
Ham (2018)		Constraint Programming	✓			Up to 100	Cplex	C++
Bouman et al. (2018)		Dynamic Programming	✓			Agatz et al. (2018)	Cplex	Java
Sawadsitang et al. (2018)	IP	L-shape Decomposition	✓				Cplex	
Wang and Sheu (2019)	MILP	Branch and Price	✓			Up to 15	Gurobi	C#
Tang et al. (2019)		Constraint Programming	✓			Bouman et al. (2018)	Cplex	Python
Dell'Amico et al. (2021b)	MILP	Mathematical Programming	✓			Up to 72	Cplex	
Schermer et al. (2020)	MILP	Branch and Cut	✓			Up to 20	Gurobi	
Roberti and Ruthmair (2021)	MILP	Branch and Price	✓			Up to 39	Cplex	C
Zhu et al. (2024a)	MILP	Branch and Price	✓			Up to 10	Cplex	Python
Tamke and Buscher (2021)	MILP	Branch and Cut	✓			Agatz et al. (2018)	Gurobi	C#
Pugliese et al. (2020)		Mathematical Programming	✓			Up to 100	Cplex	Java
Dukkanci et al. (2021)		Second-Order Cone Programming	✓			Up to 30	Cplex	Java
Boccia et al. (2021)	ILP	Branch and Cut and a Column Generation	✓			Murray and Chu (2015)	Cplex	C
Vásquez et al. (2021)	MIP	Benders Decomposition	✓			Up to 20	Gurobi	Python
Cavani et al. (2021)	MILP	Decomposition Approach and a Branch and Cut	✓			Up to 24	Cplex	C
Zhu et al. (2022)	MILP	Branch and Price	✓			Up to 25	Cplex	Python
Di Puglia Pugliese et al. (2021)		Benders Decomposition	✓			Up to 100	Cplex	Java
Dell'Amico et al. (2021a)		branch and bound	✓			Up to 229		
Kang and Lee (2021)		Benders Decomposition	✓			Up to 50	Cplex	Python
Momeni et al. (2022)	MILP	Augmented Epsilon Constraint, Benders Decomposition	✓			Up to 90	Cplex	
Yang et al. (2023)		Branch and Price			✓	Up to 40	Gurobi	C++
Tiniç et al. (2023)	MILP	Branch and Cut	✓			Agatz et al. (2018)	Cplex	Java
Zhou et al. (2023)	MILP	Branch and Price	✓			Up to 35	Cplex	Java
Yin et al. (2023)	MILP	Branch and Price and Cut	✓			Up to 45	Cplex	Java
Rave (2023)	MILP	Mathematical Programming	✓			Up to 28	Cplex	
Li et al. (2024)	MILP	Branch and Price and Cut	✓			Up to 35	Cplex	Java
Dienstknecht et al. (2022)	MIP	Dynamic Programming	✓			Up to 350	Cplex	
Mishra and Tiwari (2024)	MINLP	Hungarian algorithm	✓			Up to 490	Cplex	Python
Dodge et al. (2024)	MINLP	Improved Progressive Hedging Algorithm			✓	Up to 40	Cplex	
Ozden-Gurcan et al. (2024)	MIP	Mathematical Programming			✓	Up to 7	Cplex	
Tang and van Hoeve (2024)	MILP	An iterative algorithm			✓	Up to 40	Cplex	C++
Gürel and Serdarasan (2024)		Mathematical Programming	✓			Up to 13	Cplex	

multiple visits. Mbiadou Saleu et al. (2018) presented an iterative Two-Stage heuristic approach to the PDSTSP problem. The algorithm splits the customers between drones and vehicles and uses encoding and decoding to convert the solutions into customer orders and then optimizes the tours for the vehicles and drones.

Agatz et al. (2018) presented an IP for TSP-D, and they created a set of efficient heuristic algorithms, these heuristics use local search and dynamic programming to find the optimal solution. They provided a worst-case approximation rate for the heuristics and compared their evaluated performance within optimal solutions for small instances. Ha et al. (2018) investigated the TSP-D problem and minimized the cost of transportation and waiting time. They proposed two algorithms, first, the method of Murray and Chu (2015), TSP solution within local searches (TSP-LS), second, Greedy Randomized Adaptive Search Procedure (GRASP), thus showing the significant performance of GRASP over TSP-LS in finding quality solutions. Salama and Srinivas (2020) proposed an Unsupervised Machine Learning- based heuristic to solve last mile delivery with drones and a truck. They showed that they achieved better results due to clustering and routing. Baek et al. (2020) considered a Greedy Heuristic algorithm to solve a delivery problem with electric trucks and drones to minimize energy consumption. They showed that their approach can save 43%–69% energy on average in different scenarios. Nguyen et al. (2020) solved the TSP-D problem with a Monte Carlo Tree Search (MCTS) algorithm that uses random sampling and a search tree to find the optimal solution. The performance of the results was compared to instances in the benchmarks and provided an improvement in the solutions with an average solution quality of 12%. Yurek and Ozmutlu (2021) focused on the TSP-D problem with a flexible recharge policy as opposed to the traditional model with swapping. They used a heuristic approach to find the optimal solution, and they also showed that partial or full recharging can affect the efficiency of the drone and truck delivery system. Kitjacharoenchai et al. (2019) applied an Adaptive Insertion Heuristic for mTSPD and showed that their approach efficiently reduces delivery times

Daknama and Kraus (2017) proposed for VRPD a heuristic algorithm using with Two Nested Local Search, which offers a significant improvement over the basic greedy algorithm. In addition, Schermer et al. (2018) presented a Two-Phase heuristic approach for VRPDm. Their algorithm first constructs routes for vehicles and later a single-phase algorithm that uses the drone from the beginning. They explained the efficiency of the heuristics and emphasized that the results of the two-phase heuristic are better than those of the single-phase heuristic in different scenarios. Ulmer and Thomas (2018) offered a dynamic method for same-day delivery with integrated trucks and heterogeneous drones and presented a functional approximation based on geographic district division that significantly increases the number of same-day deliveries. Moreover, their approach is a Markov Decision Process framework for the challenges of the routing problem.

Luo et al. (2017) investigated 2E-GURP and solved it with two heuristic algorithms. The first heuristic constructs the visit of the destination and splits it into trucks, and the second heuristic constructs the tour of the truck and assigns the drone to it, the computational results show that the first heuristic performs slightly better, although the second heuristic is more time-saving. Another two-echelon vehicle and UAV routing problem for post-disaster humanitarian operations was solved by Faiz et al. (2020). They proposed a Column Generation-based Decomposition Algorithm which has high potential to improve humanitarian logistics under uncertain demand conditions. Hu et al. (2018) presented a Vehicle-Assisted Multi-UAV Routing and Scheduling Algorithm to solve vehicle-assisted multi-drone surveillance. Their algorithm iteratively updates a memory of drone route candidates to optimize path planning. The performance of the algorithm is effective compared to existing solutions, especially in covering distances for both vehicles and drones. Karak and Abdelghany (2019) to solve the hybrid vehicle-drone routing problem for pickup and delivery services focused on a methodology based on the Clarke and Wright algorithm and compared it with vehicle and drone-driven routing heuristics, which led to efficient cost reduction through the experiments. Poikonen and Golden (2020) provided a heuristic approach that includes three phases: Route, Transform and Shortest Path, to solve delivery scheduling and routing complexity. They showed a significant improvement in minimizing the completion time by increasing the number of drones in different scenarios. Dayarian et al. (2020) solved Same-Day-Delivery with Drone Resupply by using different strategies such as the Restricted-Resupply Strategy and the Flexible-Resupply Strategy, which improved the efficiency of same-day delivery and service rates. Delazeri and Ritt (2021) focused on TSP-MFS and proposed a method that uses a multi-armed bandit strategy for customer partitioning, a Matching-based algorithm for sort allocation, local searches for optimization, and a Greedy Scheduler for quality estimation. The superior results of the methods show that the methods are efficient in delivery systems. Meng et al. (2023) developed a Two-heuristic algorithm for solving multi-visit drone routing problems with pickup and delivery services. The proposed algorithm includes an initial payload construction and an improved simulation algorithm. Thomas et al. (2023) presented a Relax-and-Fix heuristic developed using deep learning to solve a new variant of the truck drone delivery problem, which is an effective approach to solving large-scale problems. Mulumba and Diabat (2024) used a heuristic method based on the classical Clarke–Wright Savings heuristic that improved operational efficiency by using drones in pickup and delivery systems.

Table 6 summarizes all studies that focused on heuristic methods. Based on the structure of the problems, various heuristic methods were used for modeling, most of which are deterministic models. Moreover, there is no specific heuristic approach that has been used frequently. The instances vary up to several hundreds of customers, which entails heavy computational power compared to exact methods. However, as the table shows, the recommended methods are not suitable for every type of problem, which could be a weakness of this approach.

4.3. Meta-heuristic methods

Meta-heuristic algorithms have been extensively studied in CTD-LMD as they provide remarkable improvements in delivery and cost reduction within a reasonable time. In particular, they are preferred for large problems with high complexity, where traditional methods are not effective approaches for finding optimal solutions. Ponza (2016) and Yu et al. (2023) introduced Simulated Annealing (SA) to solve FSTSP and demonstrated its high performance over the traditional methods. In addition, Boysen et al. (2018) used the SA algorithm to solve the TSP-D problem. The algorithm quickly evaluates various truck routes by addressing the drone subproblem independently, and the competitive solution generation brings significant improvement to drone-based delivery systems. Furthermore, Liu et al. (2023) has proposed a Two-Stage Heuristic algorithm based on SA to solve MD-VRPSPDNF and highlighted the potential of this algorithm to solve complex delivery problems.

AlMuhaideb et al. (2021), Caggiani et al. (2017), Gómez-Lagos et al. (2021) and Kyriakakis et al. (2023) have implemented the Greedy Randomized Adaptive Search Procedure (GRASP) algorithm to solve CTD-LMD, each of these studies on the GRASP algorithm has a different problem setting and the main differences are in the problem definition, Parking lots, different speeds, electric trucks and the number of drones. They all showed the effectiveness of the GRASP algorithm in terms of delivery time and cost compared to traditional methods.

Moshref-Javadi et al. (2020) solved TDRA with a meta-heuristic algorithm inspired by Adaptive Large Neighborhood Search (ALNS). The algorithm navigates through the solution space by using various heuristic techniques and finds the best solutions through iterations, they showed a considerable reduction in waiting times. In addition, Kitjacharoenchai et al. (2020) used a similar algorithm to solve 2EVRPD.

Table 6
Heuristic methods.

Author	Mathematical model	Method	Deterministic	Dynamic	Stochastic	Number of customers	Solver	Programming language
Murray and Chu (2015)	MILP	FSTSP: Heuristics (Savings, Nearest Neighbor and Sweep), PDTSP: Heuristics (Savings, Nearest Neighbor)	✓			Up to 20	Gurobi	Python
Agatz et al. (2018)	IP	First-cluster, Second-heuristics Based on Local Search and Dynamic Programming	✓			Up to 12	Cplex	Java
Wule et al. (2020)	MILP	Heuristic Algorithm called Heterogeneous Collaboration Vehicles Iterative Local Search	✓			Up to 150	Gurobi	Python
Jeon et al. (2021)	MILP	An Adjacent Distance-Based assignment Heuristic	✓			Up to 100	Cplex	Python
Murray and Raj (2020)	MILP	A Three-Phased Heuristic Solution Approach	✓			Up to 100	Gurobi	Python
Mbiadou Saleu et al. (2018)	MILP	An Iterative Two-Step Heuristic	✓			Up to 228 , Murray and Chu (2015)		
Ha et al. (2018)	MILP	Greedy Randomized Adaptive Search Procedure	✓			Up to 100	Cplex	
Salama and Srinivas (2020)	IP, MINLP	An Unsupervised Machine Learning-Based Heuristic	✓			Up to 35	Cplex	Python
Baek et al. (2020)		A Greedy Heuristic Algorithm	✓			Up to 30		
Nguyen et al. (2020)		Monte Carlo Tree Search	✓			Up to 100		C++
Yurek and Ozmutlu (2021)	MILP	A Heuristic Approach	✓			Up to 20	Cplex	C++
Kitjacharoenchai et al. (2019)	MIP	An Adaptive Insertion Heuristic	✓			Up to 50	Cplex	Matlab
Daknama and Kraus (2017)		Two Nested Local Search Algorithms	✓			Up to 200		Java
Schermer et al. (2018)		Two Phase Heuristic, Single Phase Heuristic				Up to 1000		
Ulmer and Thomas (2018)		Markov Model, Assignment and Routing Heuristic		✓	✓	Up to 800		
Luo et al. (2017)	IP	Construct Target Visiting Tour and Split/Construct Rendezvous Node Tour and Assign	✓			Up to 200		Matlab
Hu et al. (2018)	IP	Vehicle-Assisted Multi-UAV Routing and Scheduling Algorithm	✓			Up to 300		
Karak and Abdelghany (2019)	MIP	Extends the Classic Clarke and Wright Algorithm	✓			Up to 100	Cplex	
Liu et al. (2019)	MIP	Split Heuristic, Clustering Assignment	✓			Up to 100	Cplex	Matlab
Poikonen and Golden (2020)	IP	Heuristic Solution Approach Called Route, Transform, Shortest Path	✓			Up to 50	Gurobi	Python
Dayarian et al. (2020)		Two Phase Heuristic		✓				
Faiz et al. (2020)	MILP	Decomposition Algorithm with Column Generation Based Heuristics			✓	Up to 120	Cplex	
Delazeri and Ritt (2021)	MILP	A Multi-Armed Bandit Selection Strategy, A matching-Based Heuristic, Local Search Algorithms, A Fast Greedy Scheduler	✓			Murray and Raj (2020)		C++
Meng et al. (2023)	MILP	Two-Stage Heuristic Algorithm	✓				Gurobi	Python
Thomas et al. (2023)	MILP	Relax-and-Fix with Re-Couple-Refine-and-Optimize Heuristic/ Deep Learning-Based Clustering	✓			Up to 100	Cplex	Python
Mulumba and Diabat (2024)	MILP	Heuristic Approach Based on the Classic Clarke–Wright Savings Heuristic	✓			Up to 10	Cplex	Python
Liu, Liu, and Qi (2024)	ILP	Greedy Heuristic	✓			Up to 50	Gurobi	Python

They applied Drone Truck Route Construction (DTRC) and Large Neighborhood Search (LNS), which find the best solution by iteratively deconstructing and reconstructing the solution. They have shown that this approach is suitable for last mile challenges, especially for large instances. Moreover, 2E-VRP-TM was solved by Li et al. (2020). They applied an Adaptive Large Neighborhood Search (ALNS) and showed a remarkable improvement in delivery operations under time windows and mobile satellite concepts. Meng, Chen, and Li (2024) proposed a MIBP model that considers the interdependencies between the movements of trucks and drones, especially the energy consumption, and applied Adaptive Large Neighborhood Search for large instances, which improved services efficiently. Ren et al. (2023) proposed a MIP model

to optimize the routing and energy consumption for integrated electric vehicles with drones, they applied a Large Neighborhood Search algorithm enhanced with Q-learning (LNS-QL) for solving this complex problem and they handled medium and large instances efficiently with decreasing the cost and emissions of operations. Large Neighborhood Search algorithm enhanced with Q-Learning (LNS-QL) for dynamic decision making regarding route adjustments and mobile battery replacement. The high performance of LNS and its variants for the integrated drone and truck delivery system solution was attracted by Li, Chen, et al. (2022), Wu et al. (2022), Zhao et al. (2022) and Jiang et al. (2024). They all came to the conclusion that this approach is cost-effective and time-effective for the challenges of the last mile.

Several works have focused on Genetic Algorithm (GA) to solve the problem of truck and drone cooperation. Deng et al. (2020) used the GA algorithm to overcome the challenges of VRP with Movement Synchronization (VRPMS), Hazama et al. (2021) addressed the scheduling problem of package delivery with drones, they showed that GA efficiently finds near-optimal solutions and the processing time of GA is significantly shorter than that of IP Solver. Karaköse (2024) solved the HTMDP problem and emphasized the effectiveness of the approach in shortening delivery times.

Yetis and Karakose (2021) used a Quantum-Inspired Genetic Algorithm (QGA) to solve TSP-D with the goal of reducing the total cost while taking into account some factors such as payload capacity and battery life. Gunay-Sezer et al. (2023) combined GA and Ant Colony Optimization (ACO) to solve TSP-D. To improve route decision, a unique binary pheromone framework was introduced, which improved the quality of the solution. Das et al. (2020) introduced a novel Collaborative Pareto Ant Colony Optimization (Collaborative P-ACO) algorithm, which was compared with the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to show superior performance in minimizing travel cost and maximizing service performance. Kuo et al. (2023) proposed NSGA-II with a focus on minimizing carbon emissions and completion time. The dual goal they proposed is the speed and environmental sustainability of the last mile delivery. At the same time, Luo et al. (2021) proposed a method that integrated a Pareto Local Search with a GA considering a flexible time window to minimize costs and maximize customer satisfaction in a complex delivery system. Also, Wei et al. (2025) to solve TDVRPD-VRZ-NFZ, the authors propose a Genetic Algorithm with Variable Neighborhood Search and Learning Mechanism. This algorithm integrates chaotic map-based initial population generation, adaptive crossover and mutation, simulated annealing, and a knowledge-learning strategy to iteratively explore and refine solutions. The approach was evaluated using modified Solomon benchmark instances to demonstrate its practical efficacy.

Recent improvements in modern last-mile delivery have demonstrated the high performance of Variable Neighborhood Search (VNS) in optimization. Kuo et al. (2022) applied VNS to multi-echelon distribution systems and demonstrated its remarkable cost reductions. Campuzano et al. (2023) further explored VNS for delivery networks with drones, pointing out its high performance in terms of customer service and delivery speed. In addition, Ndiaye et al. (2023) has shown that VNS protects the environment and reduces operating costs when optimizing urban delivery systems. Madani et al. (2024) proposed an Adaptive Variable Neighborhood Search algorithm with Neighborhood Categorization to solve HTD-MVMLR. Their algorithm was compared with three variants of VNS and provided more efficiency and cost-effectiveness in last-mile delivery. Sacramento et al. (2019) presented an Adaptive Large Neighborhood Search for VRP-D and showed a remarkable saving in time. Liu et al. (2024) combined VNS with Simulated Annealing (SA) to escape local optima by periodically accepting worse solutions, thus facilitating a more comprehensive and adaptable exploration of the solution space.

Rich (2020) presented an Evolutionary Algorithm (EA) as a meta-heuristic algorithm for solving TSP-D. This algorithm is based on a tournament and clustering strategy for both trucks and drones during the routing process. They showed a significant improvement over the heuristic algorithm in terms of computational speed. Yılmaz et al. (2024) presented a novel fitness-distance-balance-based evolutionary algorithm to overcome the challenges of the TSP-D problem and showed its high performance compared to other algorithms.

Several different meta-heuristic algorithms have been considered to solve cooperative truck and drone delivery problems. Cui and Lei (2021) presented a new Artificial Bee Colony (ABC) algorithm for solving VRPD that employed Variable Neighborhood Descent (VND) with different neighborhood structures to improve the quality of the solution. Luo, Poon, et al. (2021) dealt with a multi-start tabu search algorithm to efficiently solve MTSP-MD considering the capacity and energy constraints. Kyriakakis et al. (2022) introduced Ant Colony Optimization that includes Variable Neighborhood Descent (VND) for local search to solve EVRPD with the goal of minimizing energy consumption, presenting an environmentally friendly approach in logistics. Ha et al. (2021) applied the Iterated Local Search (ILS) algorithm to TSP-MVD and found better solutions and runtimes than other algorithms. Luo et al. (2022) presented the ILS algorithm to solve OPDP-MTM and emphasized the robustness and effectiveness of the approach in time reduction. In addition, Momeni et al. (2023) proposed a Two-Phase algorithm based on the Nearest Neighborhood and Local Search while considering energy consumption and different settings, and especially optimized the routes for high-rise buildings. The memetic algorithm has been studied in several works to solve the complexity of the problem. Zhai et al. (2024) used this algorithm to solve the TSP-D problem and compared its effectiveness with other heuristics and meta-heuristics. Mara et al. (2023) applied this algorithm to solve the problem of combining electric truck and drone with the aim of shortening the delivery time, and Jeong and Lee (2023) extended the meta-heuristic algorithm with a constructive heuristic to solve the problem of hybrid truck and drone delivery, and both demonstrated the effectiveness of the meta-heuristic algorithm to handle the challenges of the urban delivery system. Gonzalez-R et al. (2024) proposed a bi-objective approach for the TmDTL where service time and environmental impact are optimized. Bian et al. (2024) developed a new MILP model for FAMS and applied a Micro-Evolutionary Algorithm which is a population-based algorithm with the structure of GA, to effectively expand the search. Pina-Pardo et al. (2024b) proposed a Tabu Search scheme to find the optimal solution for truck routes with integrated drone deliveries an Elite-based Multi-objective Improved Iterative Local Search (E-MIILS) algorithm proposed by Duan, Li, et al. (2025) to o solve the complex TMCRP-PD problem, they decomposed the multi-objective problem into two sub-problems, minimizing completion time and time windows violations and solved with several local iteration search in order to explore space effectively. Zhu et al. (2024b) proposed The ALNS algorithm to improve solutions using a combination of destructive and repair operators to iteratively refine routes. Initially, it constructs a feasible route served entirely by the Plug-in Hybrid Electric Vehicle before integrating drone deliveries to reduce delivery time. The energy constraints are managed by inserting charging stations via a feasibility restore function. Furthermore, the method incorporates a piecewise-linear approximation to accurately model nonlinear battery charge processes for partial recharges. Zhou et al. (2025) solved by assigning such customers (in traffic zones) to nearby truck routes using a K-order Nearest Neighbor Algorithm, and then constructing drone paths from truck stop points to deliver packages. This methodology guarantees that trucks circumvent restricted zones, while drones are responsible for executing last-mile deliveries. The comprehensive routing is enhanced utilizing ant colony optimization alongside simulated annealing techniques.

Table 7 summarizes all studies that deal with meta-heuristic methods. The most commonly used meta-heuristic algorithm is Variable Neighborhood Search and its variants. It is a powerful method for solving complex VRP in which the neighborhood structures are changed systemically during the search for the optimal solution. According to

Table 7
Meta-heuristic methods.

Author	Mathematical model	Method	Deterministic	Dynamic	Stochastic	Number of customers	Solver	Programming language
Ponza (2016)	MILP	Simulated Annealing	✓			Up to 200	Cplex	
Caggiani et al. (2017)	MILP	Greedy Randomized Adaptive Search Procedure Algorithm	✓			Up to 100		Python
Boysen et al. (2018)	MIP	Simulated Annealing	✓				Gurobi	VB.net
Yu et al. (2023)	MILP	Simulated Annealing	✓			Up to 100		
Rich (2020)	MIP	Evolutionary Algorithm, Constraint Programming	✓			Up to 100	Cplex	C++
Gómez-Lagos et al. (2021)	MILP	Greedy Randomized Adaptive Search Procedure Algorithm	✓			Up to 30	Cplex	
Yetis and Karakose (2021)	MILP	Quantum-Inspired Genetic Algorithms	✓			Up to 100		Python
AlMuhaideb et al. (2021)	MILP	Greedy Randomized Adaptive Search Procedure Algorithm	✓			Up to 100		Python
Kyriakakis et al. (2022)		Ant Colony Optimization	✓			Up to 50		C++
Kyriakakis et al. (2023)		Greedy Randomized Adaptive Search Procedure Algorithm	✓			Up to 75		C++
Liu et al. (2023)	MILP	A Two-Stage Heuristic Algorithm Based on Simulated Annealing	✓			Up to 100	Gurobi	Matlab
Moshref-Javadi et al. (2020)	MILP	A Large Neighborhoods Search	✓			Up to 100	Gurobi	
Kitjacharoenchai et al. (2020)	MILP	Drone Truck Route Construction and Large Neighborhood Search	✓				Cplex	Matlab
Li et al. (2020)	MILP	Adaptive Large Neighborhood Search	✓			Up to 100	Cplex	C++
Wu et al. (2022)		An Improved, Adaptive, Large Neighborhood Search Algorithm	✓			Up to 20		Python
Li, Chen, et al. (2022)	MINLP	An Adaptive Large Neighborhood Search	✓				Cplex	C++
Zhao et al. (2022)	SOCP	Three-Phased Adaptive Large Neighborhood Search Algorithm			✓	Up to 48		Matlab
Sacramento et al. (2019)	MIP	An Adaptive Large Neighborhood Search	✓			Up to 200	Cplex	Java
Deng et al. (2020)	MIP	Genetic Algorithm	✓			Up to 100		
Hazama et al. (2021)	IP	Genetic Algorithm	✓			Up to 50		Python
Jiang et al. (2024)	MILP	Tailored Adaptive Large Neighborhood Search	✓			Up to 100	Gurobi	Python
Ren et al. (2023)	MIP	A Large Neighborhood Search Algorithm Based on Q-learning, Lagrangian Relaxation Algorithm	✓			Up to 300	Gurobi	Matlab
Gunay-Sezer et al. (2023)		Genetic Algorithm and Ant Colony Optimization Algorithm	✓			Up to 250		
Das et al. (2020)	MIP	Pareto Ant Colony Optimization Algorithm, Non-Dominated Sorting Genetic Algorithm II	✓			Up to 50		Matlab
Kuo et al. (2023)	MIP	Non-Dominated Sorting Genetic Algorithm II	✓			Up to 100		
Luo et al. (2021)		Multi-Objective Genetic Optimization Approach Incorporated with a Pareto Local Search Algorithm	✓			Up to 80		
Madani et al. (2024)	ILP	Variable Neighborhood Search	✓			Up to 200	Cplex	
Kuo et al. (2022)	MIP	Variable Neighborhood Search	✓			Sacramento et al. (2019)	Gurobi	Matlab
Ndiaye et al. (2023)	ILP	Variable Neighborhood Search	✓			Up to 20	Cplex	
Campuzano et al. (2023)	MILP	Variable Neighborhood Descent and A Multi-Neighborhood Tabu Search	✓			Up to 100	Cplex	C++
Cui and Lei (2021)	MIP	A New Artificial Bee Colony	✓			Sacramento et al. (2019)		C++
Luo, Poon, et al. (2021)	MILP	Multi-Start Tabu Search Algorithm with Tailored Neighborhood Structure	✓			Up to 100	Cplex	Java
Luo et al. (2022)	MIP	Iterated Local Search	✓			Up to 100	Cplex	Python
Ha et al. (2021)	MILP	Iterated Local Search	✓			Up to 100	Cplex	C++
Momeni et al. (2023)	MILP	A two-phase algorithm based on the nearest neighborhood and local search	✓			Up to 26	Cplex	C++
Mara et al. (2023)	MIP	Memetic algorithm	✓			Up to 100	Gurobi	Julia
Jeong and Lee (2023)	MILP	Memetic Algorithm with Constructive Heuristic	✓			Up to 100	Gurobi	Python
Gonzalez-R et al. (2024)		Bi Vector Coding Scheme Inspired by Flow-Shop Scheduling Problems and Simulated Annealing Algorithm	✓			Agatz et al. (2018)		
Karaköse (2024)		Genetic Algorithm	✓			Up to 120		
Yılmaz et al. (2024)		Fitness-Distance Balance-based Evolutionary Search Algorithm	✓			Ham (2018)		
Bian et al. (2024)	MILP	Micro-Evolutionary Algorithm	✓			Up to 200	Gurobi	Python
Meng, Chen, and Li (2024)	MIBP	An Adaptive Large Neighborhood Search	✓			Up to 30	Gurobi	Python
Zhai et al. (2024)	IP	Memetic algorithm	✓			Up to 100	Cplex	
Pina-Pardo et al. (2024b)	MILP	Tabu Search	✓			Up to 100	Cplex	
Duan, Li, et al. (2025)		Elite-based Multi-objective Improved Iterative Local Search	✓			Up to 100	Gurobi	
Zhu et al. (2024b)		Adaptive Large Neighborhood Search	✓			Up to 25	Cplex	
Liu et al. (2024)	MILP	Variable Neighborhood Search combined with Simulated Annealing	✓			Up to 100	Cplex	
Zhou et al. (2025)	MILP	Combined Ant Colony Algorithm and Simulated Annealing Algorithm	✓			Up to 100	Gurobi	
Wei et al. (2025)	MILP	Genetic algorithms, Local search (VNS), Memory-based Learning, and Simulated Annealing	✓			Up to 100	Gurobi	Python

analysis in research papers, this method has been successfully applied to consider the dual-modal nature (truck and drone coordination) and synchronization constraints. This method is able to break out of the local optimum through dynamic structural changes and even hybridize with other meta-heuristic methods. In terms of problem size, meta-heuristics are usually tested on datasets with larger instances, often generated synthetically or based on benchmark instances. In terms of implementation, Python, MATLAB and C++ are the most commonly used languages as they support numerical optimization and algorithm tuning. Surprisingly, stochastic and dynamic models are either not present at all or extremely rare.

4.4. Hybrid meta-heuristic methods

Recent advances in modern delivery optimization have led to various challenges in the logistics industry that are being addressed with hybrid approaches to tackle the complexity of this delivery system. Several studies have developed hybrid methods that integrate K-means clustering and GA. Mourelo Ferrandez et al. (2016) and Zhang and Li (2023a) used GA to find the optimized route, which is integrated with K-means clustering that identifies the starting points of drones; this strategy improves delivery efficiency of delivery. In addition, K-means clustering has been integrated with other algorithms in various studies to achieve significant success, namely Chang and Lee (2018),

Lu et al. (2022) and Zhang and Li (2023b). Moreover, the combination of GA with other methods has played an important role in finding the best solutions through the optimization algorithms of Ha et al. (2020), Mahmoudinazlou and Kwon (2023), Peng et al. (2019), Wang et al. (2022) and Rinaldi et al. (2023). There have been several other papers, each presenting a unique hybrid method, Also Two-Echelon Routing Problem has been considered by Liu et al. (2020), in the study, they focused on a Two-Stage Route-based modeling approach and used a hybrid heuristic together with Simulated Annealing and a Tabu list to find the best solutions. Their approach is a significant solution for vehicle-truck cooperation in last-mile delivery, along with its challenges such as payload capacity and energy consumption, Schermer et al. (2019a) proposed a hybrid method using VNS and TS, and Gonzalez-R et al. (2020) combined an Iterated Greedy heuristic with SA to address the problem of truck and drone delivery. These studies have shown the potential of hybrid methods in addressing the challenges of urban delivery systems. Khalaj Rahimi and Rahmani (2024) developed ALNS algorithm, combined with ϵ-Constraint and Weighted-sum methods, has significantly improved both the objective value and the solution time compared to other methods. Recently, Mirzapour Al-e Hashem et al. (2024) has developed a robust optimization model and applied a hybrid Meta-heuristic algorithm, which is a combination of Adaptive Large Neighborhood Search, Clarke and Wright Saving Algorithm and Genetic Algorithm. The proposed approach shows the practical application in truck drone delivery services. Mara et al. (2024) used an Adaptive Memetic Algorithm (AMA) to solve EVDRP which combined genetic algorithms, local search, and a Q-learning-based adaptive operator selection to explore and refine solutions efficiently. Their method demonstrates superior performance compared to existing approaches in terms of both solution quality and scalability. Meng, Li, et al. (2024) proposed a two-stage stochastic model to solve VRP-D, incorporating soft time windows and variable truck travel times. The first stage focuses on planning delivery routes, while the second stage adjusts truck waiting times according to real travel conditions to minimize penalties. To address the complexity of this problem, a hybrid Meta-heuristic method is employed, combining iterated greedy and simulated annealing techniques, and utilizing a sample average approximation method to manage uncertainty.

Table 8 summarizes all studies dealing with hybrid Meta-heuristic methods. Table presents the handling of larger instances with hybrid Meta-heuristics, which mainly includes Hybrid Genetic, K-means Clustering and Large Neighborhood Search. Hybrid methods combine the global search performance of Meta-heuristics with local improvement strategies or embedded exact solvers (e.g., MILP subroutines with Gurobi or CPLEX). The table shows that the instances treated with this approach are between 30 and 450 and are mostly implemented in Python or Matlab. Deterministic models remain dominant due to their simplicity and compatibility with most heuristic and Meta-heuristic solvers, while there are only two studies that include stochastic elements and no dynamic model.

4.5. Other methods

Several papers dealt with different methods to solve the complexity of this delivery system. Wang et al. (2017) had an analysis by several theorems and a comparison in different scenarios, Yurek and Ozmutlu (2018) introduced a Decomposition- based Iterative Optimization algorithm to solve TSP-D and showed the potential of the algorithm in improving logistic delivery problems. Dell'Amico et al. (2020), Schermer et al. (2019b) and Zhao et al. (2025) presented a matheuristic and showed that this method offers high performance on small and medium instances. Bakir and Tiniç (2020) presented a temporally extended network model for the VRPFD problem and discussed that this model is not feasible for larger instances. Therefore, they introduced a Dynamic Discretization Discovery (DDD) algorithm that creates a temporally extended subnetwork and iteratively refines it until the best solution is found. Zhang et al. (2024) used continuous approximation models to determine the expected distances and costs for each delivery method and highlighted that the use of drones in a hybrid model with trucks can significantly reduce the cost compared to truck- only delivery. Pina-Pardo et al. (2021) investigated at TSPRD-DR that a decomposition approach was introduced to the problem of truck redelivery of new orders by drones from the depot, which is effective in last-mile delivery. Moshref-Javadi et al. (2023) designed a simulation model to optimize same-day delivery. The model utilized transshipment points where drones can deliver packages to points and trucks can pick up the packages from these points and deliver them to customers, they increased the effectiveness of delivery by reducing the need for trucks to return to the depot. In addition, Wu et al. (2021) proposed a reinforcement Learning (RL) method to overcome the challenges of truck and drone. Kong et al. (2023) presented a novel self-directed reinforcement learning structure, the Constraint-based Hybrid Pointer Network (CH-Ptr-Net), which combines the embedding of a Graph Neural Network (GNN) and an attention decoder. This model uses MILP to determine the best sequence of deliveries to handle the dynamics of delivery route optimization. They compared the high performance of this model with other approaches based on less flexible, exact or heuristic methods. Ghiasvand et al. (2024) focused on MTDRP under uncertain demand and proposed a Two-Stage Clustering Algorithm that incorporates Multiple-kernel and single-kernel Learning based methods that provide a data-driven robust optimization model and enable significant improvement of the delivery system. Pina-Pardo et al. (2024a) applied a route-based Markov Decision Process (MDP) in conjunction with an online policy to optimize real-time decision making. Imran and Won (2024) developed a method to use machine learning and heuristics to find the best solution for VRP-D under dynamically changing traffic conditions. Boccia et al. (2024) introduced a matheuristic approach that combines elements of the exact method (branch and cut) and heuristic techniques. This method involves solving the TDTLP on a reduced graph by fixing the order of customer visits, which significantly reduces the complexity of the problem. In addition, Liu, Liu, and Qi (2024) designed Benders decomposition to split the problem into smaller subproblems and handle the uncertainty efficiently and used Sample Average Approximation (SAA) with historical data to estimate the uncertainty of travel time and Robust Optimization (RO) for worst-case scenarios to ensure resilience to the most extreme uncertainties. She and Ouyang (2024) proposed a system under air traffic congestion that uses partial differential equations (PDEs) to model the coordination of drones and trucks, and they used A Physics-Informed Neural Network (PINN) approach to solve these equations efficiently, and the solutions are used to optimize key parameters such as truck speed and drone deployment. Duan, Li, et al. (2025) proposed a deep reinforcement learning methodology employing the Pointer Network (Ptr-Net) to solve C-TDRP with a focus on vehicle obstacle avoidance. This paradigm leverages an encoder–decoder architecture augmented with attention mechanisms to refine delivery route optimization, conceptualizing the task within a sequence-to-sequence learning framework. The method exhibits adaptive learning capabilities that effectively diminish delivery costs and energy consumption, demonstrating notable improvements over conventional heuristic approaches. Bogyrbayeva et al. (2025) proposed Reinforcement Learning for VRP-D as a Markov Decision Process (MDP) and applies a reinforcement learning approach. An attention-based encoder and a group-aware LSTM decoder to coordinate are used, which learn a stochastic policy through interaction with the environment and is trained using the Reinforce algorithm with a critic baseline for variance reduction for large-scale their method enables to solve effectively.

Table 9 summarizes all works that focus on other methods. It demonstrates the utilizing emerging or non-traditional solution approaches such as Machine Learning (ML), dynamic optimization techniques, Reinforcement Learning (RL) and Matheuristics for various customer groups up to 229. These advanced methods are used for

Table 8
Hybrid Meta-heuristic Methods.

Author	Mathematical model	Method	Deterministic	Dynamic	Stochastic	Number of customers	Solver	Programming language
Mourelo Ferrandez et al. (2016)		K-means with Genetic Algorithm	✓			Up to 100		Matlab
Zhang and Li (2023a)		K-means Clustering and the Extended Non-Dominated Sorting Genetic Algorithm-II	✓			Up to 120	Cplex	Matlab
Chang and Lee (2018)	NLP	K-means Clustering and TSP Modeling, Nonlinear Programming and Shift-Weights	✓			Up to 30		
Lu et al. (2022)		Two-Stage Heuristic Formulated on Bisecting K-means	✓			Up to 150		Python
Zhang and Li (2023b)		K-means, TSP modeling, Tabu Search	✓			Up to 100	Cplex	Matlab
Ha et al. (2020)		Hybrid Genetic	✓			Murray and Chu (2015), Ha et al. (2018)		C++
Peng et al. (2019)	MILP	Hybrid Genetic	✓			Up to 450		
Wang et al. (2022)	MILP	the Adaptive Large Neighborhood Search, Hybrid Genetic-Sweep Algorithm, and Variable Neighborhood Search	✓			Up to 50	Cplex	
Mahmoudinazlou and Kwon (2023)		Genetic Algorithm, Dynamic Programming, and Local Search.	✓			Agatz et al. (2018)		Julia
Rinaldi et al. (2023)	MILP	Hybrid Genetic, An Alternative ad-hoc Greedy	✓					
Liu et al. (2020)		Tabu Search and Simulated Annealing	✓			Up to 100		
Schermer et al. (2019a)	MILP	Variable Neighborhood Search and Tabu Search	✓			Agatz et al. (2018)	Gurobi	
Gonzalez-R et al. (2020)	MILP	Iterated Greedy Heuristic with Simulated Annealing	✓			Up to 250	Gurobi	Python
Khalaj Rahimi and Rahmani (2024)	MILP	An Adaptive Large Neighborhood Search combined with ϵ-Constraint and Weighted-sum	✓				Cplex	Matlab
Mirzapour Al-e Hashem et al. (2024)		Combining Adaptive Large Neighborhood Search, Clarke and Wright Saving Algorithm, and Genetic Algorithm			✓	Up to 41	Cplex	Matlab
Mara et al. (2024)		Meta-heuristics (memetic algorithm, genetic operators, local search) and machine learning (Q-learning-based adaptation)	✓			Up to 100	Gurobi	Python
Meng, Li, et al. (2024)		Meta-heuristic integrating the Sample Average Approximation			✓	Up to 100		Python

complex and uncertain problems and Python is preferred as the predominant programming language due to its scientific libraries, more flexible and open-source research tools.

Solving CTD-LMD requires addressing unique coordination and synchronization constraints. In examining and analyzing research on solution approaches, it has been shown that heuristic methods are simple and provide quick feasible solutions, although they do not provide high-quality results. Most of the research papers that focus on heuristic methods are not able to explore the solution spaces. However, the works that have applied meta-heuristic methods to this modern delivery problem are able to navigate large and multimodal search spaces and find near-optimal solutions to large problems by maintaining the balance between exploration and exploitation. In contrast, exact methods such as branch-and-bound or branch-and-cut provide a great improvement for MILP models and guarantee optimality but just for small and medium-sized instances. Recently, hybrid methods and other advanced methods, including machine learning, have gained prominence in CTD-LMD, especially in learning cost approximations or guiding heuristic/metaheuristic search strategies through reinforcement learning or neural graph networks. These hybrid and learning methods offer adaptive and data-driven decision-making capabilities, but are not yet able to guarantee optimality. Therefore, all investigated methods are a promising solution for CTD-LMD solutions.

5. Challenges

Recently, researchers have focused on the challenges of this modern delivery system. However, many challenges require further investigation to have an effective and reliable impact on the delivery system. Some future study directions of the studied papers have been identified and summarized in Table 10. There are also three main categories for challenges: Uncertainty, Drone, and Problem-oriented. Each category has its own subsections that provide details about the expansion and future direction.

5.1. Uncertainty based

In truck and drone delivery, uncertainty is a key challenge that can affect efficiency, planning and reliability. This challenge arises from

Table 9
Others.

Author	Mathematical model	Method	Deterministic	Dynamic	Stochastic	Number of customers	Solver	Programming language
Wang et al. (2017)		Analysis on Several Worst-Case Scenarios	✓					
Yurek and Ozmutlu (2018)	MIP	Heuristic: Decomposition Iterative Algorithm	✓			Up to 20	Cplex	C++
Bakir and Tiniç (2020)	MILP	Dynamic Discretization Discovery Approach	✓			Up to 25		Python
Schermer et al. (2019b)	MILP	Matheuristic	✓			Up to 100	Gurobi	
Dell'Amico et al. (2020)	MILP	Matheuristic	✓			Up to 229	Gurobi	C
Zhao et al. (2025)	MILP	Matheuristic	✓				Gurobi	C
Pina-Pardo et al. (2021)	MILP	Dynamic Decomposed into Truck-Routing and the Drone-Resupply Parts	✓			Up to 50	Cplex	Java
Moshref-Javadi et al. (2023)		Developed a Simulation Model	✓		✓			
Wu et al. (2021)	MIP	Reinforcement Learning	✓			Up to 200		Python
Zhang et al. (2024)		Continuous Approximation Models	✓					
Kong et al. (2023)	MILP	Self-driven Reinforcement Learning Structure			✓	Up to 50		Python
Ghiasvand et al. (2024)	MILP	Two-Stage Clustering Algorithm with Multiple-Kernel and Single-Kernel Learning-Based Methods			✓	Up to 80	Cplex	Python
Pina-Pardo et al. (2024a)		Route-Based Markov Decision Process			✓	Up to 100	Cplex	Python
Imran and Won (2024)		A Heuristic Algorithm and Machine Learning		✓		Up to 50		Python
Boccia et al. (2024)	MILP	Matheuristic	✓			Up to 75	Gurobi	Python
Liu, Liu, and Qi (2024)		Stochastic and Robust Optimization with Benders Decomposition			✓	Up to 25	Cplex	Python
She and Ouyang (2024)		Physics-Informed Neural Networks			✓	Up to 200		Python
Duan, Li, et al. (2025)	MILP	Deep Reinforcement Learning (DRL) with a Pointer Network (Ptr-Net)	✓			Up to 120		Python
Bogyrbayeva et al. (2025)	MILP	Reinforcement Learning	✓			Up to 50	Gurobi	

unpredictable or dynamic factors, most notably weather, traffic and demand, which have been cited for truck and drone coordination.

- Weather conditions can significantly affect both truck and drone delivery. In particular, uncertain weather makes it difficult to operate drones, as they are susceptible to strong winds, cold and heat. These issues can reduce battery efficiency by leading to shorter flight range, overheating and the risk of damage or failure. To address this problem, the prediction accuracy needs to be improved and the mathematical model needs to be adapted to these conditions by taking into account battery life, payload capacity management, weather resistance, speed and energy consumption. Advanced techniques can be used, such as dynamic optimization, where the variable decisions and constraints are dynamically updated according to the latest weather data, or machine learning algorithms. The stochastic optimization model shows different results under different scenarios. In addition, a simulation can help to see the results and how the model can be affected by different weather conditions to achieve high accuracy in the analysis. Sawadsitang et al. (2018) considered the uncertainties such as the weather conditions for cooperative drones and trucks during delivery, as the weather conditions can affect drone take-off or breakdowns during delivery. They presented a three-stage stochastic model for breakdown and drone launch scenarios. Campuzano et al. (2023) focused on speed and weather conditions and improved the effectiveness of operations by taking into account aspects such as wind and energy consumption and how lower speed can reduce completion time through more drone use. Weather uncertainties, especially wind direction and speed, which affect the drone's travel time, were also investigated in detail by Mirzapour Al-e Hashem et al. (2024) and Dodge et al. (2024).
- Traffic is a challenge that can significantly affect the delivery process and the reliability of drone and truck. Traffic brings with it various issues, such as longer delivery times, costs and fuel consumption, environmental impact, customer satisfaction, and drone deployment and retrieval. In addition, traffic can affect the mathematical modeling of the problem. As traffic reduces speed and increases fuel consumption, the objective function must be dynamically adjusted or include uncertainties for unpredictable traffic conditions. Yang et al. (2023) focused on this challenge and developed a robust model that accounts for the uncertainty of road traffic for drone and truck delivery with the aim of reliable and efficient services. In addition, Imran and Won (2024) designed a heuristic method that incorporates a machine learning-based travel time prediction model to dynamically estimate the travel time between different locations under traffic conditions. In addition, Duan, Li, et al. (2025) modeled traffic through a time-dependent road network, affecting the vehicle's travel speed based on time of day, to address this constraint, they utilized a function of departure time and traffic conditions with a piecewise-defined speed function. Zhou et al. (2025) and Wei et al. (2025)

addressed traffic by modeling restricted traffic zones where trucks are not allowed to enter. Customers located in these areas must be served by drones instead.
- Real-time ordering or uncertain demand is a complex challenge where the model needs to be dynamically adjusted based on order updates. Depending on the changing conditions, robust or stochastic optimizations can be applied to deal with the uncertainty. Also, simulation techniques can be used to recognize different conditions under uncertain demand. Dayarian et al. (2020), Ghiasvand et al. (2024), Moshref-Javadi et al. (2023), Ulmer and Thomas (2018) and Pina-Pardo et al. (2024a) considered uncertain demand and same-day delivery, which provides insight into improving the future drone delivery system.

5.2. Drone based

Drones in last-mile delivery face particular problems, especially in coordination with trucks, take-off and landing, payload limitations and energy consumption, which are being addressed in numerous research papers for future studies on last-mile delivery.

- Improving the launch and return capabilities of drones on different fixed platforms (at or away from the customer) or on moving platforms such as trucks can increase the complexity of drone delivery implementation. Sharing a drone fleet and multiple trucks, the truck deciding whether to wait for the drone to return or go to another location and pick up the drone later to make the system more flexible, launching and picking up at any points along the arc between two customers, and the separate launch and pickup time of drones are the challenges of this system that can be a groundbreaking approach to this sophisticated delivery system.
- Drones with different capacities can carry parcels ranging from light to heavy and bring flexibility and efficiency to the delivery system. However, the decision of which drones to use for parcels must be based on size and weight. This challenge as future work has been mentioned in several articles Kitjacharoenchai et al. (2020), Luo, Poon, et al. (2021), Murray and Raj (2020), Ulmer and Thomas (2018) and Rinaldi et al. (2023). In contrast, drones with heterogeneous characteristics were solved as a constraint of Kang and Lee (2021), Murray and Raj (2020), Thomas et al. (2023), Ulmer and Thomas (2018), Zhao et al. (2022).
- Energy consumption and the charge or replacement of batteries pose a major challenge for this delivery system in real-life scenarios. Energy consumption was considered in several studies (Baek et al., 2020; Campuzano et al., 2023; Dukkanci et al., 2021; Gonzalez-R et al., 2020; Kong et al., 2023; Kuo et al., 2023; Kyriakakis et al., 2023, 2022; Liu et al., 2020; Luo, Poon, et al., 2021; Mara et al., 2023; Meng, Chen, & Li, 2024; Momeni et al., 2023, 2022; Mourelo Ferrandez et al., 2016; Poikonen & Golden, 2020; Ren et al., 2023; Roberti & Ruthmair, 2021; Tamke & Buscher, 2021; Zhang & Li, 2023a; Zhou et al., 2023; Zhu et al., 2022, 2024a) and Li et al. (2024). Energy consumption and charging play a decisive role in environmental sustainability and cost minimization.

5.3. Problem based

According to recent studies, the collaboration of trucks and drones in last-mile delivery is promising, but it struggles with various issues such as time windows, alternative objectives, integration of electric trucks and drones, and security and privacy issues that need to be studied in depth to create a more realistic scenario for application in the real world of delivery.

- Time window, a challenge mentioned in some posts, recently addressed by Deng et al. (2020), Ham (2018),Das et al. (2020), Duan, Li, et al. (2025), Kong and Jiang (2024), Kong et al. (2023), Kuo et al. (2023, 2022), Li, Chen, et al. (2022), Li et al. (2024, 2020), Liu et al. (2024), Meng, Li, et al. (2024), Pugliese et al. (2020), Wei et al. (2025), Yang et al. (2023), Yin et al. (2023), Zhang and Li (2023a) and Meng, Chen, and Li (2024). The need for pick-up and delivery was also mentioned as a challenge in several contributions and solved by Ham (2018), Karak and Abdelghany (2019), Luo et al. (2022) and Jiang et al. (2024), Khalaj Rahimi and Rahmani (2024), Kyriakakis et al. (2023), Liu et al. (2023), Meng, Chen, and Li (2024), Meng et al. (2023), Mulumba and Diabat (2024), Zhang and Li (2023b), and Li et al. (2024). Multi-depot has not yet been adequately addressed in studies of truck and drone delivery cooperation, and it is a suspect challenge that remains to be investigated. Expanding the problem to include multiple depots can increase coverage by serving more customers in less time. However, this requires advanced planning for coordination between depots.
- Alternative objectives for cooperative trucks and drones delivery in e-commerce pose challenges. Although most studies are based on time or cost minimization, some works focus on other objectives such as multi-objective system (Das et al., 2020; Duan, Li, et al., 2025; Gonzalez-R et al., 2024; Khalaj Rahimi & Rahmani, 2024; Kuo et al., 2023; Luo et al., 2021; Zhang & Li, 2023a), maximum order (Dayarian et al., 2020; Pina-Pardo et al., 2024a; Ulmer & Thomas, 2018) and energy consumption (Kyriakakis et al., 2023, 2022; Zhu et al., 2024a) and minimum service delay (Zhao et al., 2025). Exploring alternative destinations is crucial for the advancement of delivery systems in many ways, such as environmental sustainability, efficient operations, enhanced customer experience, scalability, and improved competitiveness in logistics companies.
- The integration of electric trucks and drones is a forward-looking approach for enhanced last-mile delivery processes. Moreover, this eco-friendly transportation is crucial for sustainability as it reduces resource consumption, emissions and other negative environmental impacts. Recently, this delivery problem has been addressed in several papers (Baek et al., 2020; Kyriakakis et al., 2022; Mara et al., 2023; Ren et al., 2023; Zhu et al., 2022, 2024a, 2024b) and Mara et al. (2024). However, further studies need to be carried out to overcome the challenges and make the future of delivery systems more sustainable and efficient.
- In CTD-LMD, security, data protection, and privacy are important issues that need to be considered from both a legal and technological perspective. There are increasing concerns about data protection when using drones in public and private spaces, especially when monitoring and collecting data. The vulnerability of drones can lead to security concerns for people, such as hacking, hijacking and data breaches that could disrupt the delivery process. Safety concerns also include the risk of malfunction, mid-air collisions and dangerous landings, especially in residential areas. Addressing these challenges with CTD-LMD requires close collaboration between technology developers and regulators.

These ongoing challenges open up several promising questions for future research:

- How can AI-based models be applied to weather, traffic, and uncertain demand for this modern last-mile delivery problem?
- What models and methods can ensure the feasibility of balancing energy consumption during delivery operations?
- What is the optimal location for the drone to synchronize the take-off and return of the drone, especially for dynamic truck routes, and which algorithm can be applied effectively?
- How can the time window remain feasible or the delay be minimized in restricted weather or traffic conditions?

Table 10
Challenges.

Future directions	Papers
Weather Condition	Ulmer and Thomas (2018), Faiz et al. (2020), Kang and Lee (2021), Campuzano et al. (2023), Yin et al. (2023), Kyriakakis et al. (2022), Yılmaz et al. (2024), Kong and Jiang (2024)
Traffic Conditions	Caggiani et al. (2017), Wang and Sheu (2019), Yin et al. (2023), Campuzano et al. (2023), She and Ouyang (2024), Yılmaz et al. (2024), Kong and Jiang (2024), Bogyrbayeva et al. (2025)
Uncertain Demand, Real Time Orders	Sawadsitang et al. (2018) , Das et al. (2020), Wu et al. (2022), Wang and Sheu (2019), Meng et al. (2023), Gonzalez-R et al. (2024), Mirzapour Al-e Hashem et al. (2024), Meng, Chen, and Li (2024), Boccia et al. (2024), Liu, Liu, and Qi (2024), Dodge et al. (2024), Ozden-Gurcan et al. (2024), She and Ouyang (2024), Yılmaz et al. (2024), Duan, Li, et al. (2025), Kong and Jiang (2024), Mara et al. (2024), Liu et al. (2024), Bogyrbayeva et al. (2025), Zhou et al. (2025)
Launch and Return of Drone	Murray and Chu (2015), Moshref-Javadi et al. (2020), Das et al. (2020), Wu et al. (2022), Ndiaye et al. (2023), , Kyriakakis et al. (2022), Moshref-Javadi et al. (2023), Bian et al. (2024), Meng, Chen, and Li (2024)
Heterogeneous Drones	Ulmer and Thomas (2018),Kitjacharoenchai et al. (2020), Murray and Raj (2020), Luo, Poon, et al. (2021), Rinaldi et al. (2023), Ozden-Gurcan et al. (2024)
Time Windows, Pick up and Delivery, Drone's Capacity, Multiple Depots	Daknama and Kraus (2017), Chang and Lee (2018), Deng et al. (2020), Kitjacharoenchai et al. (2019), Liu et al. (2020), Wang and Sheu (2019), Yu et al. (2023) Kitjacharoenchai et al. (2020), Faiz et al. (2020), Tamke and Buscher (2021), Wule et al. (2020), Mirzapour Al-e Hashem et al. (2024), Pina-Pardo et al. (2021), Luo, Poon, et al. (2021), Boccia et al. (2024), Mishra and Tiwari (2024), Ozden-Gurcan et al. (2024), She and Ouyang (2024), Wei et al. (2025)
Energy Consumption, Batter Swap/ Recharging	Tamke and Buscher (2021), Mourelo Ferrandez et al. (2016), Schermer et al. (2019a),Murray and Raj (2020),Wu et al. (2021), Yurek and Ozmutlu (2018), Luo et al. (2021), Wu et al. (2022), Kyriakakis et al. (2022), Tiniç et al. (2023), Zhou et al. (2023), Gunay-Sezer et al. (2023), Jiang et al. (2024), Kyriakakis et al. (2022), Jeong and Lee (2023), Zhu et al. (2024a), Kyriakakis et al. (2023), Ghiasvand et al. (2024), Gonzalez-R et al. (2024), Mirzapour Al-e Hashem et al. (2024), Imran and Won (2024), Boccia et al. (2024), Liu, Liu, and Qi (2024), She and Ouyang (2024), Yılmaz et al. (2024), Tang and van Hoeve (2024), Zhao et al. (2025), Wei et al. (2025), Zhou et al. (2025)
Security, Safety, Regularity and Policy Framework	Mourelo Ferrandez et al. (2016), Jiang et al. (2024), Agatz et al. (2018), Wang et al. (2017), Caggiani et al. (2017), Schermer et al. (2018), Boysen et al. (2018), Bouman et al. (2018), Hu et al. (2018), Peng et al. (2019), Poikonen and Golden (2020), Liu et al. (2019), Schermer et al. (2020), Ha et al. (2020), Wule et al. (2020), Wu et al. (2021), Yetis and Karakose (2021), Vásquez et al. (2021), Cui and Lei (2021), Luo et al. (2022), Kyriakakis et al. (2023), Rave (2023), Kuo et al. (2023), Madani et al. (2024), Mirzapour Al-e Hashem et al. (2024), Ozden-Gurcan et al. (2024), Khalaj Rahimi and Rahmani (2024), Yu et al. (2023), Gürel and Serdarasan (2024), Mara et al. (2024), Meng, Li, et al. (2024)
Objectives	Murray and Chu (2015), Wule et al. (2020), Dukkanci et al. (2021), Jeon et al. (2021), Moshref-Javadi et al. (2023), Luo, Poon, et al. (2021), Kuo et al. (2023), Zhang et al. (2024) ,Mara et al. (2023), Khalaj Rahimi and Rahmani (2024), Boccia et al. (2024), Liu, Liu, and Qi (2024), Yılmaz et al. (2024), Mara et al. (2024), Bogyrbayeva et al. (2025)

- How can the limited payload of drones be combined with the capacity of trucks to ensure efficient delivery?
- How can alternative objectives such as the impact of uncertainty, service coverage, delivery delays and energy consumption be integrated into a multi-objective model for last-mile delivery?
- What models and approaches can be considered for electric trucks and drones to achieve optimal energy consumption in this environmentally friendly delivery system?
- How can the security and privacy issues of delivery by truck-drone be addressed to offer people reliability?

6. Conclusion

The integration of truck and drone delivery systems can play a key role in the logistics industry. This modern delivery system not only reduces time and costs, but also provides an environmentally friendly delivery system by reducing CO2 emissions. This integrated delivery model, with its obvious benefits, is not without its challenges, which many contributors have proposed solutions to overcome. As technological advancements continue, future research is expected to focus on the further integration of sophisticated computational techniques and the enhancement of data analytics. Developments in machine learning and artificial intelligence are projected to yield novel insights and improved efficiency through more effective analysis of expansive datasets, the automation of intricate decision-making processes, and the refinement of algorithmic precision. These technological advances possess the potential to enhance route optimization, demand forecasting, and dynamic resource allocation, which are essential for efficient delivery operations. As these innovations mature, they are expected to cultivate a more robust and adaptable logistics network capable of responding quickly to evolving consumer demands and supply chain disruptions. In addition, ethical considerations and sustainability will be pivotal in ensuring that technological progress aligns with societal needs and environmental objectives. Ongoing research and development will be critical in sustaining momentum and adapting to the continuously evolving technological landscape.

Table A.1
Abbreviation.

Abbreviation	Full name
EM-DRP-PD	Energy Minimizing Drone Routing Problem with Pickups and Deliveries
TD	Truck-Drone
CTDRSP-ELR	Collaborative Truck–multi-Drone Routing and Scheduling Problem with en Route Launch and Recovery Operations
CTD-LMD	Collaborative Truck and Drone in Last Mile Delivery
CVP-D	Carrier Vehicle Problem with Drone
DDP	Drone Delivery Problem
DRP-T	Drone Routing Problem with Truck
DO	Drone Operations
EVDRP	Electric Vehicle–Drone Routing Problem
EVRPD	Electric Vehicle Routing Problem with Drones
ERDDP	Energy Minimizing and Range Constrained Drone Delivery Problem
FDTSP	Flexible Drones Traveling Salesman Problem
HDTRP	Heterogeneous Drone-Truck Routing Problem
GADOP	Ground and Aerial Delivery Service Optimization and Planning
K-MVDRP	K-Multi-Visit Drone Routing Problem
MDVRPSPDNF	Multivisit Drone-Vehicle Routing Problem with Simultaneous Pickup and Delivery Considering No-Fly Zones
MTSP-MD	Multi-Visit Traveling Salesman Problem with Multi-Drones
Mo-CRPTW-mD	Multi-Objective Truck-Drone Collaborative Routing Problem Considering Flexible Time Windows and Multiple Drones
MDRP-PD	Multi-Visit Drone Routing Problem for Pickup and Delivery
MDVRPSPD	Multi-Visits Drone-Vehicle Routing Problem with Simultaneous Pickup and Delivery Service
MFS-VRPD	Multi-Visit Flexible-Docking Vehicle Routing Problem
FSTSP	The Flying Sidekick TSP
FS-TSP	The Flying Sidekick Traveling Salesman Problem
FSTSP-B	The Flying Sidekick TSP with Backhauls
mTSP	Multiple Traveling Salesman Problem
TDEVRP-D-SMBS	Time-Dependent Electric Vehicle Routing Problem with Drone and Synchronized Mobile Battery Swapping
PDSTSP	Parallel Drone TSP
TSP	Traveling Saleman Problem
TSP-D	The Traveling Salesman Problem with Drones
TSPRD-DR	The Traveling Salesman Problem with Release Dates and Drone Resupply
TSP- MFS	Traveling Salesman Problem with Multiple Flying Sidekicks
TSP-MD	Traveling Salesman Problem with Multiple Drones
TSPmD	Traveling Salesman Problem with Multiple Drones
TDCDP	Truck Drone Coordinate Delivery Problem
TDRP-SA	Truck and Drone Routing Problem with Synchronization on Arcs
TDHRP-TDRTT	Truck–Drone Hybrid Routing Problem with Time-Dependent Road Travel Time
TD-DRPTW	Truck-Based Drone Delivery Routing Problem with Time Windows
VRP-D	The Vehicle Routing Problem with Drones
2E_GURP	Two-echelon GV and UAV Cooperated Routing
2E-RP-T&D	Two-Echelon Routing Problem for Truck and Drone
2EVRPD	Two Echelon Vehicle Routing Problem with Drones
2E-GUCRP	Two-Echelon Ground Vehicle and its Mounted Unmanned Aerial Vehicle Cooperative Routing Problem
2EVRP-HD-UAV	Two Echelon Vehicle Routing Problem with Hotspot and Delivery UAVs
2E-VRP-TM	Two-echelon Vehicle Routing Problem with Time Windows and Mobile Satellites
HVDRP	The Hybrid Vehicle-Drone Routing Problem
MTRPD	The Multi-Trip Traveling Repairman Problem with Drones
ATSP-D	The Drone-Assisted Variable Speed Asymmetric Traveling Salesman Problem
CVDDN	The Collaborative Vehicle-Drone Distribution Network
OPDP-MTMV	The One-to-One Pickup and Delivery Problem with Multi-Trucks and Multi-Visit Drone
TSPDP	Truck-Drone Routing Problem for Parcel Delivery Services Aided by Parking Lots
TDRP	Truck–Drone Routing Problem
RDTDP	Robust Drone-Truck Delivery Problem
RTSP-mD	Robust Traveling Salesman Problem with Multiple Drones
VURA	Vehicle-Assisted Multi-UAV Routing and Scheduling Algorithm
VRP	Vehicle Routing Problem
VRPMS	VRP Extension with Movement Synchronization
VRPFD	Vehicle Routing Problem with Flexible Drones
VRPDR	Vehicle Routing Problem with Drone Resupply
VRP-DTW	Vehicle Routing Problem with Time Window
VD-ARP	Vehicle–Drone Arc Routing Problem
VRPTWD	Vehicle Routing Problem with Time Window
GV	Ground Vehicle
UAV	Unmanned Aerial Vehicle

(*continued on next page*)

Table A.1 (*continued*).

Abbreviation	Full name
IP	Integer Programming
MIP	Mix Integer Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
MIBP	Mixed Integer Bilinear Program
INLP	Integer Nonlinear Programming
SOCP	Second Order Cone Programming
HTD-MVMLR	Hybrid Truck-Drone Delivery System with Multi-visits and Multi-Launch and Retrieval Locations
MTDRP	Multi-Trips Tuck–Drone Routing Problem
HTMDP	Hybrid Truck Multi-Drone Problem
TmDTL	Truck–Multidrone Team Logistics Problem
HCVTSP	Collaboration of Heterogeneous Vehicles on Traveling Salesman Problem
TDTL	Truck Drone Team Logistic
STRPD	Simultaneous Traveling Repairman Problem with Drones
TSP-MVD	Traveling Salesman Problem with Multi-Visit Drone
DHDR	Drone Hybrid Delivery Routing
MAFS	Feasibility-assured Mothership System
EVTSPD-FF	Electric Vehicle Traveling Salesman Problem with Drone with Full Battery Capacity with Fixed Time
mDPD-T	Multi-Visit Drone-Assisted Pickup and Delivery Problem with Time Windows
VRPSDP-TDH	Vehicle Routing Problem with Simultaneous Delivery and Pickup and Temporary Drone Heterogeneity
TSP-DR	Traveling Salesman Problem with Drone Resupply
DRMTP	Drone Resupply Model with Transshipment Points
VRPRD-DR	Vehicle Routing Problem with Release Dates and Drone Resupply
DTSP-DR	Dynamic Traveling Salesman Problem with Drone Resupply
MHTDRP-PD-R	Multi-objective Hybrid Truck-Drone Routing Problem with Pickup and Delivery Services
DAPDP	Drone-assisted Pickup and Delivery Problem
2E-RP-TD	Two-Echelon Routing Problem for Parcel Delivery by Cooperated Truck and Drone
VRPD-DT	Vehicle Routing Problem with Drones under Dynamically Changing Traffic Conditions
BEVTSPD	Battery Electric Vehicle Traveling Salesman Problem with Drone
DADR	Delivery Assisted by Drone Resupply DADR
DTCO	Drone-Truck Combined Operations
TMCRP-PD	Time-dependent Multi-Objective Collaborative Routing Problem with Simultaneous Pickup and Delivery
PHEVTSPD	Plug-In Hybrid Electric Vehicle Traveling-Salesman Problem with Drone
C-TDRP	Collaborative Truck–Drone Routing Problem
VRPTW-MD	Vehicle Routing Problem with Time Windows and Multi-visit Drone
TDVRPD-VRZ-NFZ	Time-Dependent Vehicle Routing Problem with Drones under Vehicle-Restricted Zones and No-Fly Zones

It is undeniable that these significant improvements will reshape the future of last mile delivery and that further research will be required to investigate the challenges. This paper addressed the conditions of CTD-LMD and discussed research gaps. If logistics companies embrace this innovation, they can offer a more sustainable delivery ecosystem.

CRediT authorship contribution statement

Milad Faramarzzadeh: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Şener Akpinar:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Table A.1.

Data availability

No data was used for the research described in the article.

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