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# Collaborative Truck-Robot Deliveries: Challenges, Models, and Methods

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## Abstract

Robot-based urban last-mile deliveries have recently attracted increasing attention from scientific research and industry. In particular, truck-robot delivery models are emerging as viable and competitive operational approaches. Consequently, this study reviews and analyzes the challenges, models, and methods associated with collaborative truck-robot deliveries. This article begins with a brief discussion of technical aspects, application areas, and challenges for introducing this novel technology. It then reviews the research on two primary models for robot delivery, namely hub-based and truck-based, along with their typical variants. It presents fundamental mathematical models that underpin the coordination and synchronization of trucks and robots in last-mile delivery scenarios, which can serve as the backbone for solving truck-robot delivery problems. Finally, this article summarizes both exact and heuristic methods employed to optimize delivery routes, discusses the critical problem in truck-robot collaborative delivery, and provides an outlook for future developments in robot-based logistics. This article will give researchers insights into the latest advancements in problem modeling and solution methods for truck-robot collaborative delivery systems. By using the basic mathematical models summarized in the article, researchers can easily construct and solve related problems. Logistics enterprise managers will obtain an in-depth understanding of the opportunities and challenges faced when deploying the system, as well as evaluations of the system's performance in terms of operational costs, service time, and applicability. These insights provide critical references for developing effective operational strategies.

**Keywords:** Logistics, Truck-robot collaborative delivery, Robot-based delivery, Survey

# 1 Introduction

Due to population growth, sustainable and efficient transportation has become essential in ensuring economic development, improving citizens' quality of life, and decreasing pollution levels. Especially for urban areas, traffic congestion, and pollution have become one of the biggest challenges they face (World Economic Forum, 2020). The internet economy has led to a continuous increase in online orders, especially in cities. Last-mile deliveries have become a significant challenge for retailers and logistics service providers (Boysen et al, 2021). It is expected that by 2030, the last-mile service in urban areas will increase by 78% (World Economic Forum, 2020), and these services usually require the use of urban transportation networks to deliver goods to customers, increasing the urban traffic burden, thereby hindering the further improvement of citizens' quality of life. Thus, cities must find new delivery concepts to reduce costs, speed up traffic flow, reduce pollution, improve customer satisfaction, and respect labor rights. In recent years, using drones or robots for delivery has entered the vision of decision-makers (Dienstknecht et al, 2022). Compared with drone delivery, using robots for last-mile delivery in urban areas is safer and less restricted Yu et al (2020).

Recent technological developments such as 5G telecommunication networks, sensors, the Internet of Things, and artificial intelligence have opened multiple possibilities and applications for robot-based distribution (Aleksy et al, 2019; Ding et al, 2021; Wang et al, 2022). Especially based on the development of large language models, the robot's understanding ability has been substantially improved (Zhang et al, 2023; Huang et al, 2023). Robot-based logistics and deliveries have become an important aspect for the potential future transformation and upgrade of logistics enterprises and could dramatically change operations as we know them today. In addition to the progress in automated warehousing by companies such as Amazon and Alibaba, which utilize warehouse robots to automate the processes of picking, sorting, and navigation (Ng et al, 2020), an increased number of experiments with robot deliveries can be observed. For example, JD.com, Starship Technologies, and TwinswHeel have conducted robot distribution tests in specific areas (Li, 2017; Xinhua, 2018; Andrew, 2019; TwinswHeel, 2022).

The COVID-19 pandemic has sparked a surge in the public interest and demand for robot delivery as it can offer contactless delivery. Consequently, consumers, companies, and governments have transformed from wary beta testers to keen early adopters (Pani et al, 2020). Overall, autonomous delivery robots can improve efficiency, reduce costs, reduce environmental impact, and enhance brand image. Still, they face challenges regarding technology, regulations, social acceptance, safety, and others (Rai et al, 2022).

Due to technological limitations and safety concerns, it is still difficult for robots to complete the full delivery process from a distribution center to the final customer, as this requires human supervision or interaction. Therefore, robots are often confined to specific areas for delivery, such as university campuses or specific areas of a city. Scholars have explored multi-echelon truck-robot delivery systems as a new research topic. In multi-echelon delivery systems where robots are used for last-mile deliveries, the robots might be stationed at inner-city distribution centers, leading to so-called

hub-based robot deliveries. This mode would involve transporting the goods to the hub through trucks, after which the robots stationed there would deliver the goods to the designated customers. The robots can also be based on vans or trucks, leading to a truck-based delivery model. In this mode, a truck would perform as a mobile platform for carrying and supplying the robots, and the trucks and robots would perform tasks in series and parallel.

We aim to address the following research questions through this work:

- What is the general context of collaborative truck-robot urban deliveries? More specifically: what are the currently available technologies, what are potential application areas, and what challenges need to be overcome?
- How can collaborative truck-robot deliveries be organized? In more detail: what concepts are proposed in the recent scientific literature and how are they modeled?
- What methods are used to solve these models?

We, therefore, provide an introduction to some of the technical details, applications, and overall challenges encountered by such delivery concepts before examining models and algorithms to solve the resulting routing problems in detail. This literature review provides a classification of different existing problem variants of combined truck-robot deliveries with a strong emphasis on mathematical modeling. In the operations research literature, in-depth reviews and classifications exist for a multitude of problems related to our subject of study: last mile delivery concepts (Boysen et al, 2021), two-echelon vehicle routing (Sluijk et al, 2022), green freight transportation (Bektaş et al, 2019). A systematic literature review of robot-driven deliveries proposing a broad topic overview can be found in Srinivas et al (2022). Our approach is unique as it examines in detail the models and algorithms required for collaborative truck-robot routing and thereby aims to provide a detailed entry point for future work on this fascinating research topic. Figure 1 shows the current challenges and solution models for truck-robot collaborative delivery.

The remainder of this paper is structured as follows: Section 2 will introduce the technical details, applications, and challenges of robot-based logistics; Section 3 will describe the hub-based and truck-based robot delivery models and their variants, and Section 4 will review the exact and heuristic solution approaches for these types of problems. A discussion will be presented in Section 5, and Section 6 will conclude.

## 2 Technical details, application and challenges of robot-based logistics

In this section, we will introduce some technical details for robot deliveries. Then, we will survey the potential of robot-based deliveries in various applications such as food and beverage delivery, healthcare services, retail and e-commerce, and postal services and mail delivery. Finally, we will present the legal challenges, infrastructural challenges, public acceptance challenges, and profitability challenges for the deployment of robot-based delivery in urban logistics.

Table 1 lists robots used in last-mile delivery and their technical details and application areas.

**Table 1** Robot applications

Company	Type of robot	Weight (pounds)	Speed (Km/h)	Capacity (chambers)	Delivered product	Location
PostBOT (Bonn and Bad, 2017)	4-wheel	150	6	1	P	German
DelIRo (Baum et al, 2019)	4-wheel	110	6	m	P, F	Japan
Amazon Scout (Dimensions, 2019)	6-wheel	50	24	1	P	USA
Kar-go robot (Pranjall, 2020)	4-wheel	220	96	1	M	UK
Xiaomanly (Chou, 2021)	4-wheel	220	20	m	G	China
Rakuten robot (Rakuten, 2021)	4-wheel	/	4	m	G	Japan
Domino robot (Domino, 2021)	4-wheel	80	20	1	F	USA
+DROBO (Mathieu, 2021)	4-wheel	/	40	1	M	USA
JD.com (Ahmad, 2022)	4-wheel	220	15	m	G	China
Starship Technologies (Starship, 2022)	6-wheel	22	6	1	F, G, P	USA, UK, etc
Ottobot (Ottonomy, 2023)	4-wheel	50	16	1	P	USA

Note: "F" represents Food, "G" represents Grocery, "P" represents Parcel, "M" represents Medicine, and "D" represents Documents.

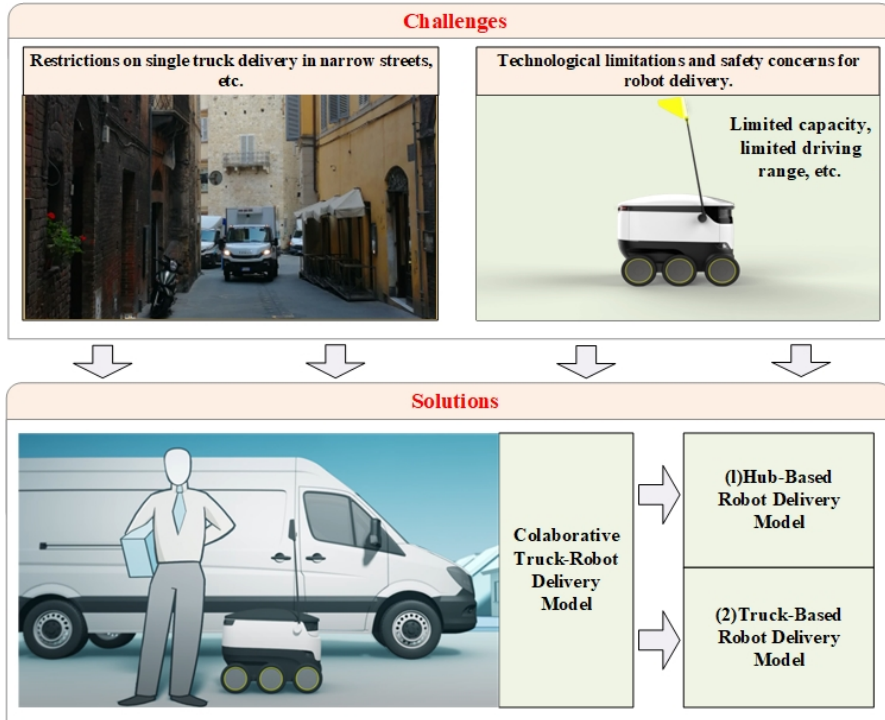


Fig. 1 Current challenges and solution models for truck-robot collaborative delivery

## 2.1 Technical details

Truck-robot collaborative distribution utilizes trucks and robots to deliver goods from a dispatch point to their destination, which requires some technical support. First, some technical details regarding robot delivery will be presented, followed by the specifics of collaborative truck-robot robot delivery.

### 2.1.1 Technical details for robot delivery

Robotic delivery technology has been boosted by the recent advances in autonomous driving technology, which encompasses a controller, a network for controller communication, a device for measuring motion, sensors for perceiving the environment (such as cameras, lasers, radars, etc.), a system for locating the position, and algorithms for driving autonomously. (Chan, 2017; Cho et al, 2021).

Recent studies have shown that robot technology has become increasingly appropriate for real applications. Delivery robots can move by themselves on sidewalks and bike lanes, but they can also be controlled remotely if there are any issues (Heimfarth et al, 2022). Delivery robots are usually used for the final part of the delivery process. In practical applications, when a robot reaches a delivery point, it calls the customers. The customers enter a code to open the robot's relevant compartment and then retrieve the goods (Yu et al, 2022b).

Small robots have low speeds and a limited capacity for short-distance deliveries. For instance, the Starship Technology delivery robot (Starship, 2017) has only one compartment with a maximum cargo weight of 10 kg. It can travel up to 6 km at a maximum speed of 6 km/h and an average effective service speed of 3 km/h. The Amazon Scout (Dimensions, 2019) is slightly larger, with the dimensions of 30 inches (76.2 cm) in length, 24 inches (61 cm) in width, and 29 inches (73.7 cm) in height. It weighs 45 kg (110 lbs.) and can carry a payload of 23 kg (77 lbs.). It can reach a maximum travel speed of 24 km/h (15 mph). In contrast, bigger robots, such as the ones used by JD.com for delivery (JD.com, 2022), have several compartments and can carry heavier loads for longer distances. The JD.com delivery robot has a weight of 400 kg and a maximum cargo weight of 100 kg. It can travel up to 50 km at a maximum speed of 25 km/h and an average effective service speed of 10 km/h. Some existing technologies can enable faster delivery robots, such as the Kar-go robot (Pranjall, 2020) and the +DROBO robot (Mathieu, 2021). The Kar-go robot, developed by the British company Academy of Robotics, can reach a maximum speed of 96 km/h, and the +DROBO robot has a maximum speed of 40 km/h.

### 2.1.2 Technical details for truck-based robot delivery

Since the robots use autonomous driving technology, the actual traveling speed usually cannot reach their design's upper limit for safety. As a result, they are generally operated at pedestrian speed. In addition, the robots' load capacities and travel distances are limited, so they cannot deliver directly to customers from the warehouse. Given the potential drawbacks of robot-only deliveries, such as limited speed and capacity, several companies have been investigating concepts of combining robots (or drones) with vans (or trucks). One example of such an approach is the concept presented by Mercedes-Benz, in collaboration with Starship Technologies, to develop a mothership approach, where each truck carries one or several robots (Matt, 2016; Starship, 2016). The challenge of this technology lies in how to ensure that the system can coordinate and synchronize the work of trucks and robots as well as among robots. This involves multiple aspects, such as hardware and software. For example, on the hardware side, a stable communication network, GPS system, perception sensors, etc., are required; on the software side, highly reliable and available autonomous driving algorithms and coordination scheduling algorithms are needed.

The current technologies permit the en-route charging of vehicles. Mobile charging platforms to charge drones have already been examined (Yu et al, 2019); in addition, mobile charging vehicles to charge other vehicles (Huang et al, 2014; Cui et al, 2018; Yu et al, 2022a) have also been tested. En-route charging technology usually requires the platform that provides en-route charging service to have the following characteristics: first, a large-capacity energy storage system that can meet the charging needs of multiple devices; second, a charging interface that can effectively connect with the devices; third, a stable charging environment, such as one that allows fixing the devices or adjusting its own settings to adapt to different scenarios; fourth, a monitoring system, power management system, rescue system, and so on, to ensure the safety and efficiency of the charging process.

## 2.2 Application areas

Many companies currently use robots in the commercial and public sectors to deliver goods and services. Some goods are delivered by robots alone, while others are delivered by a collaborative system of trucks and robots. Typical scenarios where robots deliver alone include food and beverage delivery and healthcare services. These goods are often prepared in restaurants or hospitals and delivered to customers directly. The customers' needs are sent straight to restaurants or hospitals, which usually have enough supplies or raw materials. Typical scenarios involving truck-robot collaborative delivery include retail and e-commerce and postal services, including mail delivery. These goods are often transported to a nearby hub by truck and then delivered to customers by robots quickly. The customers' needs are sent directly to large retailers or post offices, which use trucks to move them to the terminal hub through a multi-level distribution network and then use robots to deliver them to customers. Here, we only discuss the practical application scenarios of truck-robot collaborative delivery without distinguishing the various delivery systems involved. For a specific system distinction, we refer to Section 3. Of course, robot-based delivery also has the potential for large-scale application in other fields, such as cases where robots are used in fields such as production scheduling (Goli et al, 2021) or waste disposal (Tirkolaee et al, 2023).

### 2.2.1 Applications of robot delivery

**Food and beverage delivery:** Logistics robots have also been deployed in food delivery companies, particularly in the online food ordering sector, to enhance the responsiveness and security of food delivery services (minimizing human interference during transit). In March 2016, Domino's Pizza Inc., a U.S.-based pizza chain, showcased what it claimed to be the world's first autonomous pizza delivery vehicle. DRU, or Domino's Robotic Unit, was the vehicle's name (Domino, 2021). Domino's would be the first in a series of companies announcing a delivery robot that could operate on sidewalks. In response, many other food companies launched robot takeaway services; for example, Sodexo and Starship teamed up to introduce a robot delivery service at George Mason University in May 2019. The service started with 12 robots, making it the biggest campus-based autonomous robot delivery service at that time (Starship, 2019).

**Healthcare services:** Delivery robots can reduce human error in drug delivery by using a more efficient regulatory system. In other words, they can deliver drugs with greater reliability and accuracy. Many medical supplies, such as blood samples and medications, are small, lightweight, high-value, and urgent. Robots can provide a promising and efficient mode of transport for these items. For example, in 2020 in London, the autonomous delivery robot Kargo, developed by the British startup Academy of Robotics, was tested in delivering medicine (Pranjall, 2020). Kargo uses a combination of advanced robotics and driverless vehicle technology to cut up to 90% of the costs associated with the last mile of delivery. It can travel at 60 mph (96 km/h) and can carry up to 48 packages. Being electric, it takes about 3 hours to recharge fully. It can see in all directions up to 100 meters at all times. Another example is



+DROBO, a robot coupled with a drone that delivers medicines and test kits, such as the COVID-19 test or blood oxygen tests (Mathieu, 2021). The robot has four wheels, an electric motor, and a battery that provides 6 to 8 hours of continuous use.

## 2.2.2 Applications of truck-robot collaborative delivery

**Retailing and E-commerce:** E-commerce and express delivery services can employ delivery robots to offer customers round-the-clock delivery options that are convenient, efficient, and cost-effective. Some major online retailers, such as Amazon, Alibaba, and JD.com, often design and operate their own logistics and distribution robots for their own platforms. In June 2017, JD.com launched its distribution robot and accomplished its first delivery at Renmin University of China (Li, 2017). Since then, JD.com’s robot delivery service has expanded rapidly. By November 11, 2022, JD.com deployed over 700 autonomous vehicles for the Singles’ Day shopping festival and saw a 300% increase in the delivery orders handled by smart express vehicles, compared to 2021 (Wang, 2022). In January 2019, Amazon Scout, a six-wheeled delivery robot that works for Amazon, made its first deliveries to customers in Snohomish County, Washington (Scott, 2019). In September 2020, Alibaba unveiled its first logistics robot, Xiaomanlv, designed to tackle the “last three kilometers” challenge of delivering parcels from collection points to customers’ doorsteps. Xiaomanlv is expected to be widely used in Cainiao Station shortly (Sun, 2020). By September 2021, Xiaomanlv had achieved over 1 million delivery orders with this robot (Chou, 2021). In the same year, this robot also received the Red Dot award for 2021 (Reddot, 2021). In late 2020, Rakuten, a Japanese online retailer that delivers groceries to a supermarket in Yokosuka, south of Yokohama, cooperated with the city to test a new delivery robot (Rakuten, 2021). It gradually expanded to more cities in eastern Japan in 2022 (Tetsu, 2022).

**Postal services and mail delivery:** Some postal services have also begun to adopt robots for postal delivery to enhance efficiency and lower costs. Unlike online retailers, they often collaborate with logistics robot companies for their operations. For example, Deutsche Post has tested the PostBOT robot in Germany to accompany mail carriers on their routes and transport their shipments (Bonn and Bad, 2017). Japan Post and the Japanese logistics company Yamato used DeliRo robots developed by the company ZMP (LENA, 2020). The Swiss postal service has been testing mail delivery by robots built by Starship Technologies (INSIDER, 2016). Posten Norge is testing the future of logistical deliveries in Oslo using an Ottobot made by a company called Ottonomy (Mark, 2022).

## 2.3 Challenges for the introduction of robot deliveries

There exists a wide range of research on the topic of the adoption of technological innovations. Highly relevant research specifically focussed on the feasibility of introducing drone technologies has been done in recent years (Ali et al, 2022). We explicitly point to recent work on analyzing the interaction of technology enablers determinants with regard to drone technology adoption (Ali et al, 2023): based on a novel graph theory

matrix analysis framework, the authors conclude on the main enablers for drone technology such as economic potential (value offering), knowledge, legal matters, cultural beliefs, and stakeholders.

In the following, we will quickly explore some of these challenges specifically in relation to autonomous robot last-mile delivery: legal challenges, infrastructural aspects, public acceptance, and profitability are discussed.

### 2.3.1 Legal challenges

**Supervision:** Robot delivery faces legal challenges in public spaces. [Hoffmann and Prause \(2018\)](#) analyzed the regulatory framework and challenges surrounding robot delivery vehicles. For example, the person who controls the robot can be sued for any harm it causes to others. The producer of the robot can also be liable for any defect or negligence in the product’s design and manufacture. The owner of the robot can be responsible for any damage it does in public, even if unintentional. Therefore, it matters whether delivery robots are considered road or sidewalk vehicles.

**Data Security and Privacy:** Delivery robots need some remote supervision and control. They collect and send data through sensors to the control center. This data is important for robot operations and recording problems. This also raises data protection issues and requires compliance with laws like the General Data Protection Regulation ([Hoffmann and Prause, 2018](#)). Many delivery robots use wireless communication technologies. These connections can lead to data loss and present some vulnerabilities. Hackers could exploit these connections to attack robots and humans.

### 2.3.2 Infrastructural challenges

**Charging station networks:** One critical challenge is building charging station networks, as most robots are electric, and their efficiency depends on their access to them ([Boysen et al, 2018](#)). This infrastructure development is one of the biggest challenges for city planners who want to encourage companies to adopt these technologies. Many articles have highlighted the need for charging infrastructure and have suggested that government efforts are required to promote these technologies. Another important obstacle is the limited charging capacity, especially for light-duty electric robots. This is a predictable result of reducing the size of robots.

**Robot hubs:** Robot hubs are another challenge for applying delivery robots in infrastructure. Robot hubs are facilities that provide storage, charging, maintenance, and dispatch services for delivery robots. Robot hubs are less common than charging stations because they require a bigger investment. These facilities can improve the efficiency and safety of the delivery robots and lower operational costs and environmental pollution. However, building and managing robot hubs poses many difficulties, such as site selection, planning, design, investment, operation, and so on. Therefore, establishing and improving the system of robot hubs is an important issue for advancing the application of delivery robots in infrastructure.

**Road conditions:** Another significant challenge for infrastructure development is that the current operation of logistics robots requires optimal road conditions. Some existing traffic routes, including certain blocks, are not compatible with the road requirements for robot delivery. This creates problems for networking. Moreover, the

roads for robot delivery need regular maintenance to ensure the safety and efficiency of the robots; this also poses challenges to logistics and distribution companies.

### 2.3.3 Public acceptance challenges

Public acceptance is a major issue with regard to the wide adoption of new technologies such as robots or drones.

Several surveys have been conducted regarding delivery robots. In 2017 in the U.S. (Martin, 2017) showed that more than half of the respondents approved of the concept of delivery robots. However, this also means that nearly half of the surveyed public doubted robot delivery. In addition, compared with young people, the elderly are less accepting of robot delivery. Another study analyzes consumer preferences and willingness to pay for autonomous delivery robots, using a sample of 483 consumers in Portland (USA) (Pani et al, 2020). The study identifies six consumer segments and provides guidance for promoting the adoption of low-carbon deliveries in the last-mile. Recently Ouail Oulmakki and Khalfalli (2023) aimed at identifying the factors that affect the level of consumer acceptance of autonomous robotic delivery in urban areas in France. It shows that consumers are mostly neutral with regard to the new technology.

A special challenge is the interaction between small autonomous delivery robots and pedestrians on sidewalks. Stef (2019) studied how pedestrians accept delivery robots. The study used a model based on how easy and useful people think delivery robots are. Their study used a model based on how accessible and useful people think delivery robots are. The study also suggested that delivery robots should move and change directions slower than pedestrians to make them more predictable and less disruptive. However, this may not affect their efficiency greatly (Yu et al, 2020). Other factors like job loss or privacy may also affect social acceptance.

### 2.3.4 Profitability Challenge

Some robotics projects have been canceled due to low profitability, such as Amazon Scout, which was dropped by Amazon in January 2023 (Lim, 2023). One of the common challenges for large companies that invest in delivery robots is to balance the costs and benefits of their operation. For example, the campus delivery robot Xiaomanlv charges a small fee for its service.

Although delivery robots can promote savings due to the lack of need for human labor, they still require human supervision and maintenance. Therefore, logistics and distribution companies may have to form teams of robot operators and technicians. This raises a new question: Will the human resource cost of managing robots outweigh the efficiency gain of robot delivery? Finding a reasonable solution for the supervision of delivery robots is essential.

### 3 Concepts and models for truck-robot collaborative delivery optimization

As shown in Section 2, it is impractical for logistics robots to deliver from distant depots to urban customers alone due to technical and legal constraints and cost factors. In other words, robots tend to have limited travel distances. Therefore, the truck-robot collaborative delivery concepts have been proposed and modeled. In this section, we will discuss two truck-robot collaborative delivery concepts: hub-based robot delivery and truck-based robot delivery. We will mainly address the planning and optimization problems arising from these concepts and focus on the conceptual and modeling aspects.

#### 3.1 Hub-based robot delivery

In the hub-based robot delivery model, each hub employs several robots that depart from the hub to serve customers in the neighborhood. The goods are first delivered to the hubs by trucks, where they are assigned to delivery robots for final distribution. Depending upon whether the trucks may also be used for final deliveries to customers, we distinguish between the separate hub-based robot delivery (SHR) in Section 3.1.1 and the mixed hub-based robot delivery (MHR) in Section 3.1.2.

Table 2 shows the similarities and differences between hub-based robot delivery models. The columns *References* and *Trucks* represent the references and the number of the trucks considered. The columns *VMC* and *TW(H/S)* indicate whether a robot can serve multiple customers and whether the customers have time windows (hard time windows or soft time windows). The columns *CD* and *TVC* represent whether we consider the specific needs of the customer (such as 1kg, 2kg,...etc), or we only consider delivering the package to the customer and whether the trucks are allowed to visit customers directly. The columns *CT* and *RR* represent whether customer access restrictions (for example, some customers can only be accessed by robots, etc.) are considered and whether the robots can recharge in the model. The columns *RC* and *TC* represent whether there are capacity constraints for the robots and trucks, respectively. The columns *ST* and *NoD* represent whether the customers have defined service times and the number of depots in the model. The column *MV* represents whether the model allows the robot (truck) to perform multiple visits to the hubs (parking nodes).

**Table 2** Similarities and differences between hub-based robot delivery models

References	Trucks	VMC	TW(H/S)	CD	TVC	CT	RR	RC	TC	ST	NoD	MV
<a href="#">Liu et al (2020)</a>	n	✓	-	✓	-	-	-	✓	✓	-	1	-
<a href="#">Liu et al (2021)</a>	n	✓	-	✓	-	✓	-	✓	✓	✓	n	-
<a href="#">Bakach et al (2021)</a>	1	-	✓(h)	-	-	-	✓	-	-	✓	n	✓
<a href="#">Liu et al (2022)</a>	n	✓	-	✓	-	-	-	✓	✓	-	1	-
<a href="#">Alfandari et al (2022)</a>	1	-	✓(s)	-	-	-	-	-	-	-	1	-
<a href="#">Kloster et al (2023)</a>	n	-	-	-	✓	-	-	-	-	-	1	✓

From Table 2, we conclude that studies rarely consider systems where trucks are allowed to visit customers directly, customer access restrictions are given, and robot recharging is necessary. These practical details might deserve further exploration in future studies.

### 3.1.1 Separate hub-based robot delivery (SHR)

The SHR model is the most common type of hub-based robot delivery model and is similar to the two-echelon vehicle routing model (Sluijk et al, 2022), in which the truck does not serve the customer directly.

In the separate hub-based robot delivery model (see Figure 2), the trucks carry goods from a central depot to the hubs, where a predetermined number of robots are maintained. The robots at those hubs load the cargo, deliver the goods to several customers, and return to their hubs after completing the deliveries.

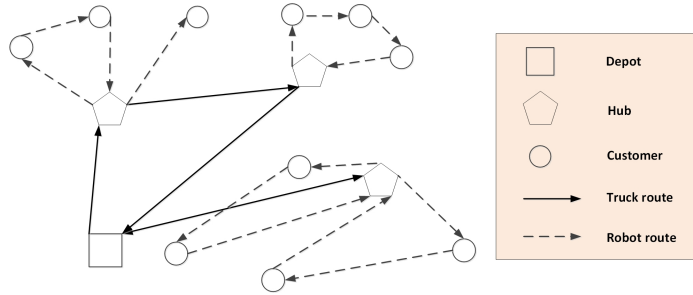


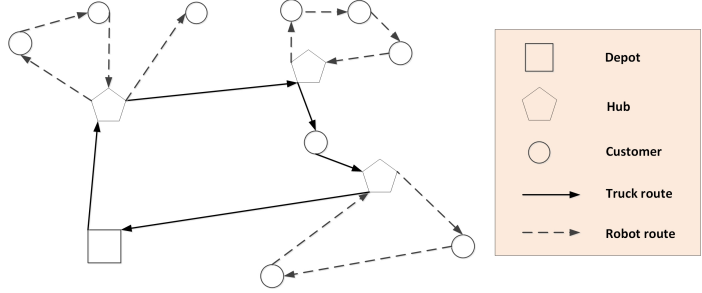
Fig. 2 Separate hub-based robot delivery model (SHR)

Bakach et al (2021) and Alfandari et al (2022) studied the hub-based robot delivery model with only one truck, while Liu et al (2020, 2021, 2022) considered multiple trucks. Bakach et al (2021) incorporated various time factors in their model, such as hard time windows, customer service times, and charging time for robots at the hubs. They allowed the robot (truck) to make multiple visits to the hubs and examined a version without time windows. The objective was to minimize the number of hubs and the robot mileage required to serve all customers, taking into account the battery capacity of the robot. Alfandari et al (2022) also investigated using customer time windows, but they accounted for soft delivery times, meaning that the delivery times can be violated with some penalties. Their objective was to minimize tardiness indicators based on customer delivery deadlines. Liu et al (2020, 2021, 2022) explored the scenario in which a robot can serve multiple customers. The models of Liu et al (2020, 2022) are similar to the classic two-echelon vehicle routing problem. The former considers a nonlinear objective function that minimizes the total transport and emission costs, while the latter aims to solve a variant of the two-echelon vehicle routing problem with heterogeneous vehicles, multiple depots, and load-dependent unit costs and emissions. Their objective was to optimize the environmental and economic performance of the distribution network while satisfying customer needs. Liu et al (2021) and Bakach et al (2021) considered multiple depots and customer service times; they

are the only ones who have addressed the customer access restrictions in the hub-based robot delivery model so far. It is also worth noting that [Bakach et al \(2021\)](#) and [Liu et al \(2021\)](#) considered multiple depot cases, while others did not.

### 3.1.2 Mixed hub-based robot delivery (MHR)

In the mixed hub-based robot delivery model shown in Figure 3, the truck is allowed to access the customer in addition to the robots.



**Fig. 3** Mixed hub-based robot delivery model (MHR)

[Kloster et al \(2023\)](#) introduced the multiple traveling salesman problem with robot/drone hubs, which is a generalization of the classical multiple traveling salesman problem. In their proposed problem, there is a depot, a set of trucks, and hubs that host a fixed number of drones/robots. The trucks depart from the depot and can replenish the hubs, which can then dispatch and operate robots/drones to serve customers. Their model allows autonomous vehicles (drones or robots) to visit the hubs multiple times. The objective is to serve all customers by truck or robots/drones while reducing the makespan (the time span from the beginning to the end of work).

### 3.1.3 Mathematical model of hub-based robot delivery model

Based on the reviewed literature, we present a fundamental mathematical model for the hub-based robot delivery problem ([Yu et al, 2022b](#)). We aimed to construct a model that can be applied to both SHR and MHR scenarios. Moreover, we wanted the model to be flexible and adaptable for further extensions. Therefore, we first defined robot customers as those who can only be served by robots. When all the customers are robot customers, it produces an SHR scenario. If some of the customers are not robot customers, we have an MHR scenario. Furthermore, we used a three-index model  $(i,j,k)$  to represent this basic model, which allows more general extensions than a two-element method. We focused on the objective function and arc constraints when developing the basic model, while other constraints, such as time flow, cargo flow, and energy flow, can be added to the basic model.

The variables and parameters used in the model are shown in Table 3.

#### (1) Objective

**Table 3** Variables and Parameters List 1

$\mathcal{V}_0$	Depot $V_0$ consists of two nodes 0 and $0'$ . Every truck route begins at node 0 and ends at node $0'$
$\mathcal{V}_r$	Set of hubs
$\mathcal{V}_c$	Set of customers
$\mathcal{V}_{c1}$	Set of truck customers, $\mathcal{V}_{c1} \in \mathcal{V}_c$
$\mathcal{V}_{rc1}$	Set of hubs and truck customer nodes, $\mathcal{V}_{rc1} = \mathcal{V}_r \cup \mathcal{V}_{c1}$
$\mathcal{V}_{rc}$	Set of hubs and customer nodes, $\mathcal{V}_{rc} = \mathcal{V}_r \cup \mathcal{V}_c$
$\mathcal{A}_1$	Truck routes, $\mathcal{A}_1 = \{(i, j) \mid i \in \{0\}; j \in \mathcal{V}_{rc1}\} \cup \{(i, j) \mid i, j \in \mathcal{V}_{rc1}, i \neq j\} \cup \{(i, j) \mid i \in \mathcal{V}_{rc1}; j \in \{0'\}\}$
$\mathcal{A}_2$	Robot routes, $\mathcal{A}_2 = \{(i, j) \mid i \in \mathcal{V}_r; j \in \mathcal{V}_c\} \cup \{(i, j) \mid i \in \mathcal{V}_c; j \in \mathcal{V}_c, i \neq j\} \cup \{(i, j) \mid i \in \mathcal{V}_c; j \in \mathcal{V}_r\}$
$\mathcal{K}$	Set of trucks, $\mathcal{K} = \{1, 2, \dots, k, \dots, K\}$ , where $K$ denotes the number of trucks, and $k \in \mathcal{K}$ indicates the $k$ th truck
$\mathcal{L}$	Set of robots, $\mathcal{L} = \{1, 2, \dots, l, \dots, L\}$ , where $L$ denotes the number of robots, and $l \in \mathcal{L}$ indicates the $l$ th robot
$d_{i,j}$	Distance between vertices $i$ and $j$
$c_1$	Truck travel cost rate
$c_2$	Robot travel cost rate
$x_{i,j,k}$	Decision variable equals to 1 if the $k$ th truck travels along arc $(i, j)$ in $\mathcal{A}_1$ , 0 otherwise
$y_{i,j,l}$	Decision variable equals to 1 if the $l$ th robot travels along arc $(i, j)$ in $\mathcal{A}_2$ , 0 otherwise
$u_i^k$	Dummy decision variable $u_i^k$ denotes the count variable for node $i$ of vehicle $k$

$$\min\left(\sum_{k \in \mathcal{K}} \sum_{(i,j) \in \mathcal{A}_1} c_1 d_{i,j} x_{i,j,k} + \sum_{l \in \mathcal{L}} \sum_{(i,j) \in \mathcal{A}_2} c_2 d_{i,j} y_{i,j,l}\right) \quad (1)$$

The objective function (1) reduces the total travel cost, which consists of the truck route cost plus the separate robot route cost.

## (2) Arc constraints

$$\sum_{(i,j) \in \mathcal{A}_1} x_{i,j,k} = \sum_{(j,i) \in \mathcal{A}_1} x_{j,i,k} \leq 1, \quad \forall j \in \mathcal{V}_{rc1}, k \in \mathcal{K} \quad (2)$$

$$\sum_{(i,j) \in \mathcal{A}_2} y_{i,j,l} = \sum_{(j,i) \in \mathcal{A}_2} y_{j,i,l} \leq 1, \quad \forall j \in \mathcal{V}_c, l \in \mathcal{L} \quad (3)$$

$$\sum_{i \in \mathcal{V}_{rc1}} x_{i,0',k} = \sum_{j \in \mathcal{V}_{rc1}} x_{0,j,k} \leq 1, \quad \forall k \in \mathcal{K} \quad (4)$$

$$\sum_{i \in \mathcal{V}_c} y_{i,s,l} = \sum_{j \in \mathcal{V}_c} y_{s,j,l} \leq 1, \quad \forall l \in \mathcal{L}, \forall s \in \mathcal{V}_r \quad (5)$$

$$\sum_{l \in \mathcal{L}} \sum_{(i,j) \in \mathcal{A}_2} y_{i,j,l} + \sum_{k \in \mathcal{K}} \sum_{(i,j) \in \mathcal{A}_1} x_{i,j,k} = 1, \quad \forall j \in \mathcal{V}_c \quad (6)$$

$$\sum_{l \in \mathcal{L}} \sum_{(i,j) \in \mathcal{A}_2} y_{i,j,l} \leq L * \sum_{k \in \mathcal{K}} \sum_{(i,j) \in \mathcal{A}_1} x_{i,j,k}, \quad \forall i \in \mathcal{V}_r \quad (7)$$

$$\sum_{i \in \mathcal{V}_r} \sum_{(i,j) \in \mathcal{A}_2} y_{i,j,l} \leq 1, \quad \forall l \in \mathcal{L} \quad (8)$$

$$x_{i,j,k} \in \{0, 1\}, \quad \forall (i,j) \in \mathcal{A}_1, k \in \mathcal{K} \quad (9)$$

$$y_{i,j,l} \in \{0, 1\}, \quad \forall (i,j) \in \mathcal{A}_2, l \in \mathcal{L} \quad (10)$$

$$u_i^k - u_j^k + 1 \leq M(1 - x_{i,j,k}), \quad \forall i, j \in \mathcal{V}_{rc1}, i \neq j, k \in \mathcal{K}, \quad (11)$$

$$u_i^l - u_j^l + 1 \leq M(1 - y_{i,j,l}), \quad \forall i, j \in \mathcal{V}_c, i \neq j, l \in \mathcal{L}, \quad (12)$$

$$0 \leq u_i^k, u_i^l \leq M, \quad \forall i \in \mathcal{V}_{rc}, k \in \mathcal{K}. \quad (13)$$

Constraints (2-10) are truck/robot arc constraints. Constraints (2-3) ensure that each node is visited by the truck/robot, at most once, and that the number of times the truck/robot leaves the node is equal to the number of times it arrives at the node. Constraints (4) ensure that the number of times the truck leaves the depot is equal to the number of times it arrives at the depot and that the number is less than 1. Constraints (5) ensure that the number of times the robot leaves a hub is equal to the number of times it arrives at this hub and the number is less than 1. Constraints (6) ensure that each customer node is visited exactly once by a truck or robot. Constraints (7) ensure that a robot cannot depart from a hub unless a truck has visited it, and vice versa. Constraints (8) indicate that the model is only allowed to use a robot once. Constraints (9-10) are binary variable constraints. Constraints (11)-(13) are Miller-Tucker-Zemlin constraints to eliminate subtours.

We can add other constraints as needed. If there is a time flow constraint or other constraints that can eliminate subtours, there is no need to add the Miller-Tucker-Zemlin constraints.

## 3.2 Truck-based robot delivery model

In this section, we will first present two typical truck-based robot delivery models: separate truck-based robot deliveries and mixed truck-based robot deliveries. Then, we will introduce the mathematical model of the truck-based robot delivery model in Section 3.2.3. Next, we will describe several typical variants of the truck-based robot delivery models in Section 3.2.4 and discuss the objective functions considered in the truck-based robot delivery system in Section 3.2.5.

Table 4 shows the similarities and differences between truck-based robot delivery models. Table 4 shows that the time window constraint is common in most truck-based robot delivery models, which reflects their application in urban logistics delivery. However, pickup and delivery and en route charging are two constraints that are rarely considered in these models, suggesting potential directions for future research.

Due to the slow speed and limited range of delivery robots, they are always paired with trucks to ensure a quick and efficient delivery by trucks transporting robots and form the truck-based robot delivery model. In the truck-based robot delivery model, a truck carries the goods to be delivered, along with the robots, and the robots are dropped off at designated parking nodes for the actual home delivery. Customers can



**Table 4** Similarities and differences between truck-based robot delivery models

	Trucks	Robots	VMC	TW(H/S)	CD	TVC	CT	PD	RR	EC	RC	TC	ST	RD	Hub	Pnode	MV	SROR
Boysen et al (2018)	1	m	-	✓(s)	-	-	-	-	-	-	-	✓	-	✓	-	✓	-	✓
Simoni et al (2020)	1	1	✓	-	✓	-	-	-	-	✓	-	-	-	-	-	-	-	✓
Yu et al (2020)	n	m	✓	✓(h)	-	-	-	-	-	✓	-	-	-	-	-	✓	-	✓
Chen et al (2021a)	n	m	-	✓(h)	✓	✓	✓	-	-	✓	✓	-	-	-	-	-	-	-
Chen et al (2021b)	n	m	-	✓(h)	✓	✓	✓	-	-	✓	✓	-	-	-	-	-	-	-
Li et al (2022a)	n	1	✓	✓(h)	✓	✓	✓	-	-	✓	✓	-	-	-	-	-	-	✓
Li et al (2022b)	1	m	-	✓(s)	-	-	-	✓	-	-	-	-	-	-	-	✓	-	✓
Ostermeier et al (2022)	1	m	-	✓(s)	-	-	-	-	-	-	-	✓	-	✓	-	✓	-	✓
Heimfarth et al (2022)	1	m	-	✓(s)	-	-	✓	-	-	-	-	✓	-	✓	-	✓	-	✓
Yu et al (2022a)	n	1	✓	✓(h)	✓	✓	✓	-	✓	✓	✓	-	-	-	-	✓	-	✓
Yu et al (2022b)	n	1	✓	✓(h)	✓	✓	✓	✓	-	-	✓	✓	-	-	-	✓	-	✓
Yu et al (2023)	n	1	✓	✓(h)	✓	✓	✓	✓	-	-	✓	✓	-	-	✓	-	-	✓
Ostermeier et al (2023)	n	m	-	✓(s)	✓	-	-	-	-	-	-	✓	-	✓	-	✓	-	✓

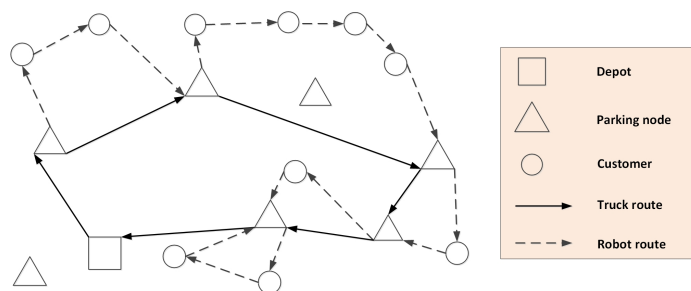
Note: The columns *Trucks* and *Robots* represent the number of trucks the model considered and the number of robots a truck can carry. The columns *VMC* and *TW(H/S)* indicate whether a robot can serve multiple customers and whether customers have time windows (hard time windows or soft time windows). The columns *CD* and *TVC* represent whether we consider the specific needs of customers and whether the truck can visit customers directly. The columns *CT* and *PD* represent whether we consider customer access restrictions (for example, some customers can only be accessed by robots, etc.) and whether there are customer pickup and delivery needs. The columns *RR* and *EC* represent whether we consider robot recharge and whether we consider en route charging in the model. The columns *RC* and *TC* represent whether there are capacity constraints for the robot and truck, respectively. The columns *ST* and *RD* represent whether the customer has service times (not fixed) and whether there are robot depots in the model. The columns *Hub* and *Pnode* represent whether there are hubs and parking nodes in the model. The columns *MV* and *SROR* represent whether the model allows the robot (truck) to make multiple visits to the hubs (parking nodes) and whether the second-level routes are open.

receive a single box or bag of groceries delivered by delivery robots. The robots can only go short distances at walking speed. The capacity of the trucks, relative to the robots and storage boxes, is limited. The key element of the truck-based robot system is the parking nodes, where the robots are released and retrieved; the parking node has no capacity for storing goods.

### 3.2.1 Separate truck-based robot delivery (STR)

Inspired by the idea of aircraft carriers, scholars have proposed the STR concept in urban distribution. The STR concept exclusively uses robots to deliver to customers without trucks. The central element of this concept is that the truck serves as the “mothership” for releasing and retrieving robots. The STR concept lowers the truck’s mileage and boosts the driver’s productivity, cutting costs and environmental impact.

Figure 4 is a schematic diagram of the separate truck-based robot delivery system. In the STR model, trucks transport their robots from the depot to the parking nodes and drop off them. Each robot visits a single customer or several customers and returns to the same or a different parking node. The trucks pick up their robots at parking nodes to load and release them again or take them to the next node. Specific studies can be found in [Boysen et al \(2018\)](#); [Yu et al \(2020\)](#); [Ostermeier et al \(2022\)](#); [Li et al \(2022b\)](#), and [Ostermeier et al \(2023\)](#).



**Fig. 4** Separate truck-based robot delivery (STR)

### 3.2.2 Mixed truck-based robot delivery (MTR)

There are many reasons for the need for human interaction in deliveries. Therefore, a human would perform the final delivery in many situations. For instance, first, some customers, such as the elderly or disabled, cannot or will not interact with the robots to retrieve their goods. Second, delivering certain goods with a robot may be illegal or unsafe. These include valuables or potentially dangerous substances. Third, individual orders may be too large for the robot compartment, for example, some home appliances, such as refrigerators, washing machines, etc. Therefore, scholars have considered a hybrid distribution system.

The MTR concept is a generalization of the STR routing problem that defines which customers a truck serves, which customers a robot approaches, and how these deliveries integrate into the delivery route. In this approach, the truck transports the

robots to the parking node, for instance, to drop off or pick up robots or go to the customer nodes to serve customers directly. However, this additional option adds to the complexity of the routing, since the number of trucks visiting the customer nodes increases the number of feasible options for first-echelon routes.

Thus, the acceptance of additional deliveries by truck creates new dependencies but raises the complexity of the problem. Figure 5 is a schematic diagram of the mixed truck-based robot delivery.

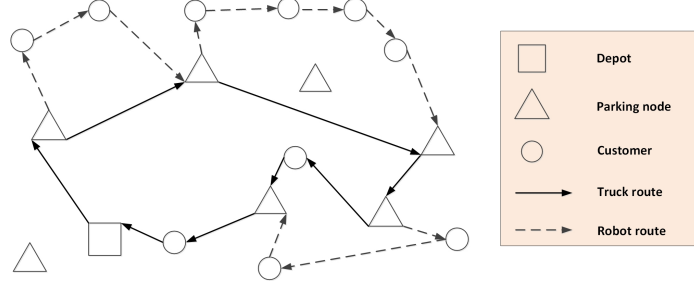


Fig. 5 Mixed truck-based robot delivery (MTR)

### 3.2.3 Mathematical model of truck-based robot delivery model

This subsection will present the mathematical model for the truck-based robot delivery problem. As in subsection 3.1.3, we aim to construct a model that can be applied to both the STR and MTR scenarios with a three-element method and focus on the objective function and arc constraints.

We have adopted the variables and parameters described in Table 3, and introduced the new or updated variables and parameters used in this model in Table 5.

#### (1) Objective

$$\min\left(\sum_{k \in F_T} \sum_{(i,j) \in A_1} c_1 d_{i,j} x_{i,j,k} + \sum_{k \in F_T} \sum_{(i,j) \in A_3} c_2 d_{i,j} (y_{i,j,k,l} - z_{i,j,k,l})\right) \quad (14)$$

The objective function (14) reduces the total travel cost, which consists of the truck route cost plus the separate robot route cost.

#### (2) Arc constraints

$$\sum_{(i,j) \in A_1} x_{i,j,k} = \sum_{(j,i) \in A_1} x_{j,i,k} \leq 1, \quad \forall j \in \mathcal{V}_{rc1}, k \in \mathcal{K} \quad (15)$$

$$\sum_{(i,j) \in A_3} y_{i,j,k,l} = \sum_{(j,i) \in A_3} y_{j,i,k,l} \leq 1, \quad \forall j \in \mathcal{V}_{rc}, k \in \mathcal{K}, l \in \mathcal{L} \quad (16)$$

**Table 5** Additional and Updated Variables and Parameters

$\mathcal{V}_r$	Set of parking nodes, note each parking node might be visited more than one time, we therefore introduce dummy nodes permitting to model multiple visits at parking nodes.
$\mathcal{V}_{rc1}$	Set of parking nodes and truck customer nodes, $\mathcal{V}_{rc1} = \mathcal{V}_r \cup \mathcal{V}_{c1}$
$\mathcal{V}_{rc1}^0$	Set of depot 0, parking nodes, and truck customer nodes, $\mathcal{V}_{rc1}^0 = \mathcal{V}_{rc1} \cup \mathcal{V}_0$
$\mathcal{V}_r^0$	Set of depot 0, and parking nodes, $\mathcal{V}_r^0 = \mathcal{V}_r \cup \mathcal{V}_0$
$\mathcal{V}_c^0$	Set of depot 0 and customer nodes, $\mathcal{V}_c^0 = \mathcal{V}_c \cup \mathcal{V}_0$
$\mathcal{A}_1$	Truck routes, $\mathcal{A}_1 = \{(i, j) \mid i \in \{0\}; j \in \mathcal{V}_{rc1}\} \cup \{(i, j) \mid i, j \in \mathcal{V}_{rc1}, i \neq j\} \cup \{(i, j) \mid i \in \mathcal{V}_{rc1}; j \in \{0\}\}$
$\mathcal{A}_2$	Robot routes, $\mathcal{A}_2 = \{(i, j) \mid i \in \mathcal{V}_r; j \in \mathcal{V}_c\} \cup \{(i, j) \mid i \in \mathcal{V}_c; j \in \mathcal{V}_c, i \neq j\} \cup \{(i, j) \mid i \in \mathcal{V}_c; j \in \mathcal{V}_r\}$
$\mathcal{A}_3$	All possible routes, $\mathcal{A}_3 = \mathcal{A}_1 \cup \mathcal{A}_2$
$\mathcal{A}_4$	Set of arcs that are unreachable by the truck, $\mathcal{A}_4 = \mathcal{A}_3 \setminus \mathcal{A}_1$
$\mathcal{L}$	Set of robots, $\mathcal{L} = \{1, 2, \dots, l, \dots, L\}$ , where $L$ is the number of robots, and $l \in \mathcal{L}$ represents the $l$ th robot. Note we assume every truck carries $L$ robots.
$y_{i,j,k,l}$	Decision variable equals to 1 if the $kl$ th robot travels along arc $(i, j)$ in $\mathcal{A}_3$ , 0 otherwise
$z_{i,j,k,l}$	Decision variable equals to 1 if the $k$ th truck with its $l$ th robot on board, travels along arc $(i, j)$ in $\mathcal{A}_1$ , 0 otherwise

$$\sum_{i \in \mathcal{V}_{rc1}} x_{i,0',k} = \sum_{j \in \mathcal{V}_{rc1}} x_{0,j,k} = \sum_{i \in \mathcal{V}_{rc1}} y_{i,0',k,l} = \sum_{j \in \mathcal{V}_{rc1}} y_{0,j,k,l} \leq 1, \quad \forall k \in \mathcal{K}, l \in \mathcal{L} \quad (17)$$

$$\sum_{k \in \mathcal{K}} \left( \sum_{(i,j) \in \mathcal{A}_3} \sum_{l \in \mathcal{L}} (y_{i,j,k,l} - z_{i,j,k,l}) + \sum_{(i,j) \in \mathcal{A}_3} x_{i,j,k} \right) = 1, \quad \forall j \in \mathcal{V}_c \quad (18)$$

$$\sum_{(i,j) \in \mathcal{A}_3} y_{i,j,k,l} + \sum_{(i,j) \in \mathcal{A}_1} x_{i,j,k} - \sum_{(i,j) \in \mathcal{A}_1} z_{i,j,k,l} \leq 1, \quad \forall i \in \mathcal{V}_{c1}^0, k \in \mathcal{K}, l \in \mathcal{L} \quad (19)$$

$$\sum_{(i,j) \in \mathcal{A}_3} y_{i,j,k,l} + \sum_{(i,j) \in \mathcal{A}_1} x_{i,j,k} - \sum_{(i,j) \in \mathcal{A}_1} z_{i,j,k,l} \leq 1, \quad \forall j \in \mathcal{V}_{c1}', k \in \mathcal{K}, l \in \mathcal{L} \quad (20)$$

$$\sum_{(i,j) \in \mathcal{A}_3} y_{i,j,k,l} \leq \sum_{(i,j) \in \mathcal{A}_1} x_{i,j,k}, \quad \forall i \in \mathcal{V}_r, k \in \mathcal{K}, l \in \mathcal{L} \quad (21)$$

$$2z_{i,j,k,l} \leq x_{i,j,k} + y_{i,j,k,l} \leq z_{i,j,k,l} + 1, \quad \forall (i, j) \in \mathcal{A}_1, k \in \mathcal{K}, l \in \mathcal{L} \quad (22)$$

$$x_{i,j,k}, y_{i,j,k,l}, z_{i,j,k,l} \in \{0, 1\}, \quad \forall (i, j) \in \mathcal{A}_3, k \in \mathcal{K}, l \in \mathcal{L} \quad (23)$$

$$x_{i,j,k} = 0, \quad \forall (i, j) \in \mathcal{A}_4, k \in \mathcal{K} \quad (24)$$

$$z_{i,j,k,l} = 0, \quad \forall (i, j) \in \mathcal{A}_4, k \in \mathcal{K}, l \in \mathcal{L} \quad (25)$$

$$u_i^k - u_j^k + 1 \leq M(1 - x_{i,j,k}), \quad \forall i, j \in \mathcal{V}_{rc1}, i \neq j, k \in \mathcal{K} \quad (26)$$

$$u_i^l - u_j^l + 1 \leq M(1 - y_{i,j,k,l}), \quad \forall i, j \in \mathcal{V}_c, i \neq j, k \in \mathcal{K}, l \in \mathcal{L} \quad (27)$$

$$0 \leq u_i^k, u_i^l \leq M, \quad \forall i \in \mathcal{V}_{rc}, k \in \mathcal{K}. \quad (28)$$

Constraints (15-25) are truck/robot arc constraints. Constraints (15-17) ensure that each node is visited by the truck/robot, at most once, and the number of times

the truck/robot leaves the node is equal to the number of times it arrives at the node. Constraints (17) ensure that the number of trucks leaving the depot is equal to the number of robots leaving the depot, and equal to the number of trucks returning to the depot and the number of robots returning to the depot. Constraints (18) ensure that each customer node is served exactly once by a truck or robot. Constraints (19-20) refer to customer nodes and depots: The same node cannot be visited by both a truck and its robot, except when the robot is on board the truck. Constraints (21) ensure that a robot is forbidden to visit the parking node unless its corresponding truck has visited it, and vice versa. Constraint (22) ensures that  $z_{i,j,k}$  is equal to 1 if and only if both  $x_{i,j,k}$  and  $y_{i,j,k}$  are equal to 1. Constraints (23) are binary variable constraints. Constraints (24-25) ensure that the arc variable is equal to 0 if access is not allowed. Constraints (26)-(28) are Miller-Tucker-Zemlin constraints to eliminate subtours.

Here, we introduce the basic constraint of arc flow. Depending on the problem’s needs, we can add other constraints, such as time flow, cargo flow, and energy flow. These constraints can also help eliminate sub-loops. If we do not consider time flow or other constraints in the model, we must add formulas to remove sub-loops.

### 3.2.4 Typical Variants

In this section, we will introduce some typical variants, such as whether the customer has a time window constraint and whether the model considers the type of customer, etc. Of course, there are many minor variants of the model, such as whether the model allows a robot to access multiple customers, whether the customer has a service time, if the model considers a hub or robot depot, and whether the hub or robot depot has an upper limit on the number of stored bots, etc. However, we will not discuss these minor variants in detail.

- **Truck-based robot delivery with time window**

Many studies have explored truck-based robot delivery with customer time window constraints (TR-TW, the separate version called STR-TW, the mixed version called MTR-TW), as robots are often used for the last mile of delivery.

Most studies have assumed hard time window constraints, meaning that the customer time window cannot be violated (Yu et al, 2020; Chen et al, 2021a,b; Li et al, 2022a; Yu et al, 2022a,b, 2023). Some researchers have also considered soft time window constraints, where the customer time window can be violated with a specific penalty in the objective function (Boysen et al, 2018; Heimfarth et al, 2022; Li et al, 2022b; Ostermeier et al, 2022, 2023). Yu et al (2023) also dealt with heterogeneous time window constraints for some customers in truck "no-go" areas: some customers have different service time windows for different vehicles.

- **Truck-based robot delivery with customer types**

Researchers have begun considering a truck-based robot delivery variant for customers with different service constraints (TR-CT). This model has two variants: a separate version (STR-CT) and a mixed version (MTR-CT). For instance, some elderly customers may prefer that human delivery staff deliver their goods directly rather than receive robotic deliveries. Figure 6 is a simple example of the MTR-CT model.

Chen et al (2021a,b) introduced a parameter to consider the customer preferences for delivery robots, which means a robot may not visit some customers. Yu et al (2022a,b, 2023) considered some customers in areas with truck access restrictions, such as pedestrian areas or university campuses. In their experiments, these customers were either evenly distributed throughout the city or clustered in a single square area, meaning that they could only be served by robots. Heimfarth et al (2022) considered more comprehensive customer types: customers with mandatory truck delivery, customers with mandatory robot delivery, and customers who can be served by trucks or robots.

- **Truck-based robot delivery without parking nodes**

Some researchers have designed truck-based robot delivery systems without parking nodes (TR-WPN) that, instead, release and retrieve robots from customer nodes, believing that some customer nodes are suitable for trucks and robots to meet. This model has two variants: a separate version (STR-WPN) and a mixed version (MTR-WPN). A simple example of MTR-WP is shown in Figure 7.

Chen et al (2021a,b) proposed an MTR-WPN problem with a time window constraint. In their model, each truck carries several robots that can be deployed to serve multiple customers at their parking nodes while the truck is serving a customer. However, each robot can only visit one customer per trip, and the truck has to wait until it collects all of its robots before leaving. Simoni et al (2020) also studied the MTR-WPN model, but they assumed that one truck carries one robot system without time window constraints. Their model allows a robot to visit multiple customers in a single trip.

- **Truck-based robot delivery with en-route charging**

The truck can provide various services to the robot, such as replenishing its cargo and charging its battery while carrying it. Some researchers have studied a variant of the MTR model that incorporates en-route charging operations (TR-EC). A mixed version of this model, called MTR-EC, is illustrated in Figure 8.

Yu et al (2022a) aimed to leverage the time that the trucks carry the robots to charge them efficiently and improve the performance of the delivery system. They proposed an electric truck-based robot delivery system with en-route charging as a way to enhance the efficiency of urban logistics. In this system, bigger electric trucks carry smaller electric robots along designated truck routes. Both the trucks and robots can deliver goods to customers directly, though some customers are only accessible by robots. The trucks stop at parking nodes where they can leave and/or get their robots and charge and fill them up if needed. The trucks can also charge their robots while driving or at any node, and the trucks themselves can be charged at the parking nodes.

Their new model revealed a novel trade-off among time, distance, and energy for electric vehicle routing. The truck’s energy use in the MTR-EC model is determined by how far it goes and how much energy it gives to its robot. Giving energy to the robot makes the truck travel less, but the robot travels more. Also, it takes time to give energy.

- **Truck-based robot delivery with pick-up and delivery**

The problem of pickup and delivery is one of the most studied problems in the field of urban logistics, and using a truck-based robot delivery system for pickup and delivery operations (TR-PD) represents a current research challenge. The separate version STR-PD and the mixed version MTR-HPD models are illustrated in Figures 9 and 10, respectively.

Li et al (2022b) studied an STP-PD model with time constraints. In their model, several robots are carried by a self-driving truck from a depot to various stations, where they are dropped off and perform multiple pickup and delivery tasks. The truck-robot collaboration faces new difficulties in meeting capacity constraints with pickup and delivery operations, as both the trucks and robots have limited loading capacities.

Yu et al (2022b) explored more complex delivery operations in the truck-robot collaboration process. They examined the variants of the MTR model that involve hybrid pickup and delivery operations (MTR-HPD). In their paper, they considered three pickup and delivery modes: The first involves collecting goods from customers and bringing them to a depot, the second involves transporting goods from a depot to customers, and the third involves moving goods from customer to other customers (with pair and precedence constraints). For the pair customers, that is, pickup-delivery-pair customers, Yu et al (2022b) distinguished among five pickup and delivery scenarios for the truck-based robot delivery system to handle them: (1) A robot transports goods from one customer to another; (2) A truck moves the goods from one customer to another customer; (3) A truck collects goods from one customer and its robot then transfers them to another customer; (4) A robot gets goods from one customer and returns to the truck-the truck then moves the goods to another customer; and (5) A robot acquires goods from one customer and goes back to the truck. The truck carries the robot and then releases it to transfer the goods to another customer.

- **Truck-based robot delivery with robot depot**

The truck-based robot delivery system enhances the flexibility of the distribution system by the trucks transporting the robots to deliver. However, loading too many robots on a truck may reduce its cargo capacity. Therefore, a promising solution is to establish small robot depots that can store robots and coordinate with the truck-based robot system (TR-RD). This model has two variants: a separate version (STR-RD) and a mixed version (MTR-RD).

Boysen et al (2018); Ostermeier et al (2022); Heimfarth et al (2022), and Ostermeier et al (2023) considered the truck-based robot delivery system with robot depots. The robot depot has the function of storing robots but not the ability to store goods. The truck carries and releases robots but does not retrieve them. In their model, a single truck carries multiple robots, and the consideration is whether the vehicle can reach customers.

Boysen et al (2018) proposed the STR-RD concept first, in which a truck loads goods and robots from a depot and drives to the city center. The truck releases the robots with goods to serve single customers. The robots deliver the goods to their assigned customers and return to the robot depots in the city center. The truck can restock the robots at these robot depots and release more of them until all its customers are served. Based on Boysen et al (2018), Ostermeier et al (2022) extended STR-RD

by adding the constraints that a set with practical relevance where the available robot fleet is limited. Ostermeier et al (2023) extended their previous model to a multi-truck form. The STR-RD problem is illustrated in Figure 11. Heimfarth et al (2022) assumed that the truck can also serve customers directly in their MTR-RD model, which is shown in Figure 12.

• **Truck-based robot delivery with hub**

Incorporating hubs into the truck-based robot delivery model is a potential option to leverage the benefits of both hub-based and truck-based robot delivery.

Yu et al (2023) proposed a hybrid (mixed) truck-based robot delivery model with hubs (MTR-H), which integrates the hub-based robot delivery model and the truck-based robot delivery model, as shown in Figure 13. The MTR-H model enables the distribution system to optimize the choice of hubs or parking nodes to maximize resource utilization and enhance distribution efficiency while complying with complex municipal regulations. They compared the performance and demonstrated the advantages and disadvantages of such an MTR-H model over the pure hub-based and truck-based robot delivery models.

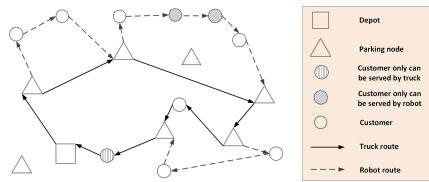


Fig. 6 MTR-CT

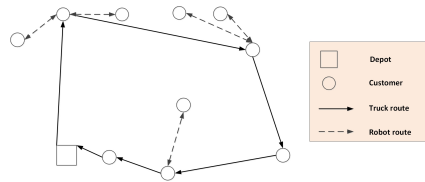


Fig. 7 MTR-WPN

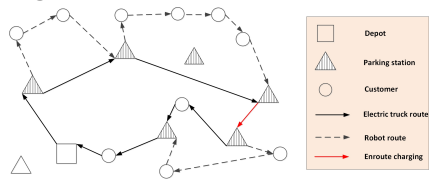


Fig. 8 MTR-EC

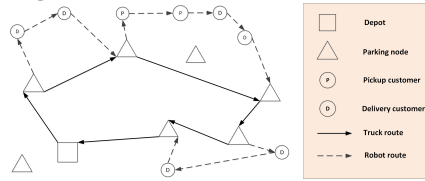


Fig. 9 STR-PD

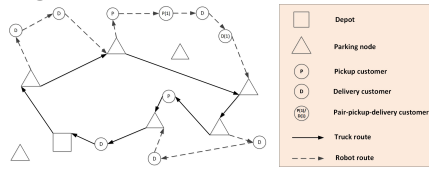


Fig. 10 MTR-HPD

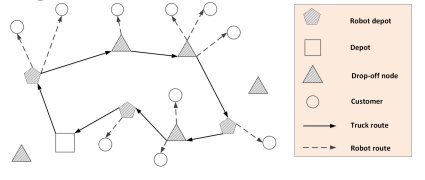


Fig. 11 STR-RD

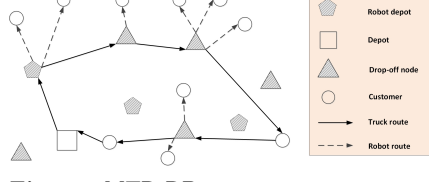


Fig. 12 MTR-RD

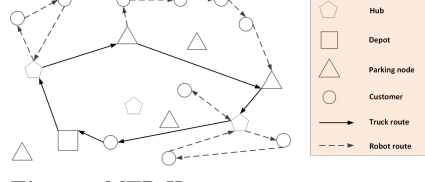


Fig. 13 MTR-H



### 3.2.5 Objective functions

To accommodate the growing demands of companies and customers, researchers have devised various objective functions to evaluate the performance of the truck-based robot delivery system. These objective functions typically involve the travel distances and travel times of trucks and robots, etc., or the number of customers who experience delays. All current research basically uses a weighted approach to transform multiple targets into a single target for modeling. Currently, almost all research uses a weighted approach to transform multiple objectives into a single objective for modeling. Table 6 shows the objective for truck-based robot delivery models.

The most common objective function in the classical VRP problem is the total weighted travel distance, which is also frequently used in the truck-based robot delivery problem. Yu et al (2020, 2022a,b, 2023) adopted this objective function, which consists of the truck weight times the truck routes plus the robot weight times the robot routes.

Another objective function that is often optimized is the travel time-based cost, which measures the total time spent by the trucks and robots in the delivery system. For instance, Simoni et al (2020) aimed to minimize the total time needed to serve all customers by either truck or robot. Similarly, Chen et al (2021a,b) sought to minimize the overall duration of the truck and robot routes.

A third typical objective function that is relevant for truck-based robot delivery systems, especially in urban areas where customers are more sensitive to delivery time windows, is the weighted number of late deliveries. Some studies have focused on minimizing this objective function-based model. For example, Boysen et al (2018), and Li et al (2022b) set their objective function to minimize delayed deliveries in the STR-based model.

In practice, distribution companies may have to consider multiple objectives simultaneously when implementing truck-based robot delivery systems. Some studies have taken this into account and proposed hybrid objective functions that combine different aspects of delivery performance. For example, Ostermeier et al (2022), and Heimfarth et al (2022) aimed to minimize the weighted total cost of travel tours, travel time, and delayed deliveries. On the basis of these objective functions, Ostermeier et al (2023) further considered the waiting cost. Similarly, Yu et al (2023) formulated their objective function as the sum of travel costs, equipment usage costs, and labor usage costs. The travel costs include the costs incurred by the trucks and robots during their routes. The equipment usage costs cover the costs of using trucks, robots, hubs, and parking nodes. The labor usage costs consist of the driving costs and waiting costs. In addition, Li et al (2022a) considered their objective function as the sum of travel distance and waiting time.

## 4 Solving truck-robot delivery problems

Common solution methods for truck-robot delivery problems can be broadly categorized into exact and heuristic methods. Exact methods can obtain the optimal solution. Frequently used exact methods in truck-robot delivery problems include mathematical programming, branch-and-cut, etc. However, due to the poor performance of exact

**Table 6** Objective for truck-based robot delivery models

	Objective
Boysen et al (2018)	Weighted delayed deliveries
Simoni et al (2020)	Total time used by trucks and robots
Yu et al (2020)	Weighted total costs of a delivery tour
Chen et al (2021a)	Overall duration of truck and robots routes
Chen et al (2021b)	Overall duration of truck and robots routes
Ostermeier et al (2022)	Weighted total cost of delivery tour, travel time, and delayed deliveries
Li et al (2022a)	Travel distance and waiting time
Li et al (2022b)	Weighted delayed deliveries
Heimfarth et al (2022)	Weighted total cost of delivery tour, travel time, and delayed deliveries
Yu et al (2022a)	Weighted total costs of a delivery tour
Yu et al (2022b)	Weighted total costs of a delivery tour
Yu et al (2023)	Minimize the travel costs, equipment usage costs, and labor usage costs.
Ostermeier et al (2023)	Weighted total cost of the delivery tour, travel, waiting, and delay times.

algorithms in solving large-scale problems, for instance, for truck-robot delivery problems based on simple constraints, current exact algorithms can only solve problems with about 25-100 coordinate nodes. Therefore, researchers often use more efficient heuristic methods to handle problems. Heuristic methods can efficiently solve problems but may sacrifice the optimality, completeness, or accuracy of the solution during the algorithm-solving process. Common heuristic methods in truck-robot delivery problems include artificial immune algorithm, local search-based algorithm, variable neighborhood search, adaptive large neighborhood search, etc. To balance the speed of solution and accuracy, some scholars use matheuristic methods to solve truck-robot collaborative delivery problems. Matheuristic methods are a combination of exact methods and heuristic methods, which take into account the accuracy of mathematical programming and the efficiency of heuristic algorithms, thereby improving the efficiency and quality of the solution.

In this section, we will first review the exact algorithms to solve the truck-robot delivery problems (In Section 4.1) and then review the heuristic algorithm for the truck-robot delivery problems (In Section 4.2). Table 7 overviews the methodologies and instances for truck-robot delivery models.

Table 7 indicates that most studies have used Mixed Integer Linear Programming (MILP) modeling and heuristic methods to solve the truck-robot delivery problem, which leaves room for further enrichment of the methods. In addition, the hub-based robot delivery model is easier to solve than the truck-based robot delivery model, and the size of the solved instances is relatively large.

#### 4.1 Exact algorithms

Most prior studies have used mixed integer programming models to formulate the truck-robot delivery problem, which can clearly represent the problem and solve small-scale instances accurately, providing a benchmark solution for algorithm comparison. [Simoni et al \(2020\)](#) also adopted integer programming to model the related problems. [Yu et al \(2020\)](#) used the column generation to calculate the lower bound of their secondary objective. However, few scholars have proposed other algorithms for the truck-robot delivery problem.

To the best of our knowledge, only [Alfandari et al \(2022\)](#) have conducted related research so far. They studied a hub-based robot delivery problem and developed an efficient branch-and-benders-cut algorithm to solve instances of a realistic size. Specifically, they introduced a novel and problem-specific normalization method for Benders decomposition. This method avoids solving Linear Programming (LP) and, instead, uses a fast combinatorial algorithm inspired by [Magnanti et al \(1986\)](#) to generate the coefficients of the Benders cut. Furthermore, they adopted a branch-and-cut approach that separates Benders cuts dynamically, rather than solving each relaxed master problem as an Integer Linear Programming (ILP), as in conventional implementations. Computational results demonstrate that this new Benders method surpasses all other options with a customized combinatorial procedure for producing Benders cuts.

**Table 7** Methodologies and instances for truck-robot delivery models

	Problem	Mathematical model	Algorithm	Number of customers
Boysen et al (2018)	STR	MILP	Multi-start local search	6,40
Simoni et al (2020)	MTR	IP	Heuristic+DP+LS	8-100
Yu et al (2020)	STR	MILP	VNS+Backtracking+Column generation	15,30,50,100
Chen et al (2021a)	MTR	MILP	ALNS	100
Chen et al (2021b)	MTR	MILP	heuristic+MILP	25-50
Bakach et al (2021)	SHR	MILP	/	100,200,300
Liu et al (2021)	SHR	MILP	Hybrid artificial immune algorithm	31,50,100
Ostermeier et al (2022)	STR	MILP	Multi-start local search	50
Heimfarth et al (2022)	MTR	MILP	General VNS	50
Li et al (2022a)	MTR	MILP	GRASP+VNS	100
Li et al (2022b)	STR	MILP	/	7,12
Yu et al (2022a)	MTR	MILP	ALNS	60
Yu et al (2022b)	MTR	MILP	ALNS	5,15,30
Alfandari et al (2022)	SHR	MILP	Branch-and-benders-cut	25-100
Yu et al (2023)	MTR	MILP	ALNS	60
Kloster et al (2023)	MHR	MILP	Iterated local search+set-partitioning	16-121
Ostermeier et al (2023)	STR	MILP	Clustering and routing heuristic with MIPs	50

## 4.2 Heuristic algorithms

The exact algorithm does not perform well for the truck-robot delivery problem in medium-scale or large-scale problems because of the complex collaboration between the trucks and robots. Therefore, efficient heuristics are often needed for studies such as larger-scale case simulations. In the following subsection, we will review the heuristic algorithms that have been used to solve the truck-robot delivery problem.

### 4.2.1 Artificial immune algorithm

[Liu et al \(2021\)](#) proposed a hybrid artificial immune algorithm for solving the multi-objective hub-based robot delivery problem. The immune algorithm preserves the good characteristics of the original algorithm while employing the concept and theory of immunity to genetic algorithms. It uses specific information or knowledge from the problem deliberately and strategically to prevent the deterioration of its optimization process. Compared with the Improved Non-dominated Sorting Genetic Algorithm (NSGA-II), the proposed hybrid artificial immune algorithm demonstrates superior performance.

### 4.2.2 Local search based

The local search starts from an initial solution and searches a predefined neighborhood of the solution. Moving to any better solution in the neighborhood and continuing the search until no improvement can be found, it returns to the current solution. Local search has several advantages, such as its simplicity, which makes it easy to understand; its flexibility, which allows it to adapt to different problems; and its ease of implementation, which requires little computational resources.

[Boysen et al \(2018\)](#) proposed a simple and effective multi-start local search procedure for the STR-TW. The procedure generates an initial tour by employing priority rules, then ensures its feasibility by considering capacity constraints, and finally improves the feasible solution by applying local search. They used their algorithm to solve instances with up to 40 customers, which is challenging for exact methods. Following a similar idea, [Ostermeier et al \(2022\)](#) proposed a heuristic that generates an initial route and improves the truck route with a specific search approach. Their approach is structured on the work of ([Boysen et al, 2018](#)), which shows efficiency for the truck-robot delivery problem to minimize lateness. However, they developed specific algorithms and operators that aimed to minimize costs to suit their setting and model. The computational results show that their approach cuts costs by up to 43%, relative to conventional truck deliveries, and by up to 22%, relative to a truck-robot system of separate rounds for truck-based robot delivery.

### 4.2.3 Variable neighborhood search

The variable neighborhood search (VNS) algorithm is a metaheuristic based on local search. By performing an alternating search using a neighborhood structure composed of different actions, it achieves a good balance between intensification and diversification. The variable neighborhood search algorithm consists of two main components, namely variable neighborhood descent (VND), which explores increasingly

larger neighborhoods around the current solution, and perturbation, which escapes from local optima by randomly modifying the solution.

Heimfarth et al (2022) developed a customized solution approach based on a general VNS. They first generated an initial truck tour depending on the problem instance. Then, they found the optimal robot schedule, using a MIP, and completed the truck route to a full solution. Next, a general VNS with a shaking step and a subsequent variable neighborhood descent was used to improve the truck routes. Their algorithm can efficiently address the routing problem and demonstrates its advantages in the MTR-CT-TW model with the complex objective function. Li et al (2022a) developed a hybrid algorithm that combines a greedy randomized adaptive search procedure and a VNS. Based on generated and benchmark instances, they conducted computational experiments to evaluate the inter-satellite synchronization, the formulation, and the hybrid algorithm.

#### 4.2.4 Adaptive Large Neighborhood Search

The adaptive large neighborhood search (ALNS) algorithm is a metaheuristic that incorporates a measure of the operator’s effect into the neighborhood search. This allows the algorithm to automatically select effective operators to destroy and repair the solution, thus increasing the likelihood of finding a better result. The ALNS algorithm has been used as a classical algorithm to solve the VRP problem, and some scholars have adapted it to address the truck-robot delivery problem.

Chen et al (2021a) proposed an improved adaptive large neighborhood search heuristic algorithm with seven removal and five insertion operators to address the MTR-WPN model with customer time window constraints. Some truck-robot delivery problems are more complex and require a focus on single-route feasibility determination during the ALNS design process. For instance, Yu et al (2022b) proposed an ALNS algorithm to solve the MTR-HPD problem with customer time window constraints (MTR-HPD-TW). Their ALNS evaluates the viability of a given route, with an emphasis on the capacity viability of the parallel routes. They noted that a parallel path is only capacity-viable if the capacity in the parking nodes, as well as the independent-truck route and robot route, are all viable. Yu et al (2022a) also proposed an ALNS algorithm to solve the MTR-EC problem with time window constraints (MTR-EC-TW), using a time-energy-route feasibility assessment method. Their problem involved a trade-off between trucks and robots regarding energy transfer and travel distance: The energy transfer decreases the travel distance of a truck but increases that of its robot, resulting in an unusual charging function. They developed heuristic methods to check the feasibility of: (1) which agents to charge, (2) how much energy to transfer, (3) where to perform the charging, and (4) when to initiate the charging. Yu et al (2023) proposed an innovative ALNS by exploring new adaptive strategies that consider the connection between the destroy and repair operators more closely and applied it to solve the MTR-H model with customer time window constraints (MTR-H-TW). Their algorithm efficiently solves large instances with ten hubs, 30 parking nodes, and 60 customers.

### 4.2.5 Matheuristics

Matheuristics are optimization algorithms that combine metaheuristics and mathematical programming techniques. Matheuristics have a certain accuracy, but they also require more solution time than pure heuristic algorithms.

Some mathematical methods are a combination of heuristics and exact algorithmic solutions; for example, [Yu et al \(2020\)](#) developed a matheuristic that combines a multi-start VNS with destroy and repair operators and a backtracking component to solve the STR-TW problem. Their matheuristic can handle instances with up to 100 customers. In addition, many mathematical methods combine heuristics and solvers; for example, [Chen et al \(2021b\)](#) designed a two-stage matheuristic for MTR-TW problems. Their method first partitions the customers into groups, where each group has one customer (or drop-off or pickup node) served by a truck and the rest served by robots. Then, each subproblem is solved by a MILP model with fewer decision variables. [Kloster et al \(2023\)](#) applied an iterated local search metaheuristic to obtain several routes and form a solution pool. Then, they used a set-partitioning model to determine the best combination of routes. [Heimfarth et al \(2022\)](#) also incorporated a MIP model into their heuristic method to evaluate and complete the truck route by finding the optimal robot schedule. [Ostermeier et al \(2023\)](#) introduced a new heuristic method: the Truck-and-Robot Clustering and Routing heuristic. This method also depends upon customized initial heuristics, problem-related neighborhood operators, and estimates that result in solvable MIPs.

## 5 Discussion

### 5.1 Discussion on practical aspects

We expect that the technology of robot delivery will become safer and more reliable, the application scenarios will expand and diversify, and the challenges will diminish.

A primary concern of robot delivery is safety. Robot delivery raises safety issues, both in terms of the robot’s physical operation and the data and information security involved. Technological advances can alleviate the former, and we anticipate the emergence of L4-level autonomous delivery robots ([FedEx, 2021](#)). The latter poses a challenge to personal and national information security due to the extensive collection of road and facility data during the robot’s operation. This challenge is hard to overcome quickly and depends largely on different countries’ laws, regulations, and policies.

Another important aspect is the application scenario of robot delivery. A promising area for robots is to enhance their accessibility for deliveries. Although many researchers have claimed that robots can perform home delivery, they cannot do so in a general sense of reality. For example, robots face difficulties in delivering goods to residents of apartment buildings. Customers must go downstairs to receive or return items, which is less convenient than traditional courier delivery. However, some novel robot technologies, such as stair-climbing and elevator robots, have enabled robots to access the same locations as couriers ([Cui et al, 2022](#)).

The challenges of legality, infrastructure, public acceptance, and profitability for robot delivery will be reduced in the future as technology, operating models, and society progress. The relaxation of relevant regulations and the improvement of infrastructure will increase the legitimacy and feasibility of robot delivery. We see more self-driving vehicles and robots on the road as proof of this. We acknowledge that the operating cost of a single robot delivering only one item to a single customer is high, but if we employ a robot that can deliver multiple items to a zone with a large customer base, such as campuses, residential areas, etc., then we can significantly reduce the operating costs of enterprises. This is the case with Xiaomanlv and other operating models currently in use in China. Currently, some groups, especially the elderly, are hesitant to accept robot delivery and prefer human interaction with couriers. With the advancement of emotional robot technology, robots can communicate verbally with customers, which mitigates some of the concerns about robot delivery. The enhancement of robot technology, the decrease in cost, and the rise in public acceptance will improve the profitability of robot delivery. The existence and expansion of many robot delivery companies in the market are positive signs of future adoption.

## 5.2 Discussion on mathematical models and solution approaches

Collaborative truck-robot delivery has attracted considerable attention and has advanced in models, algorithms, and simulations. Generally speaking, the research on effectively utilizing the truck-robot collaborative delivery model (i.e., exploring model variants) is more popular than the development of specific (exact) algorithms to solve those models. Moreover, we found only a few case studies and management insights in existing research publications. These are the directions that can be pursued in the future.

**(1) Modeling perspective:** The existing studies have mainly focused on deterministic truck-robot collaborative delivery models, including novel models with en-route operations (charging), hybrid pickup and delivery models, etc.

The hub-based robot delivery model has a delivery network similar to the two-echelon vehicle routing problem that has been extensively studied in the last decade. The main difference is that the second level of the delivery network involves delivery robots instead of the traditional human-based delivery model (humans driving conventional vehicles, riding bicycles, or walking). Therefore, future research on the hub-based robot delivery model should focus on designing and optimizing the second-level delivery network according to the features of delivery robots. For instance, based on customer preferences, a hybrid delivery fleet of humans and robots can be employed in the second level of the distribution network for differentiated services, which can enhance the adaptability of the whole distribution system.

The truck-based robot delivery model has a delivery network similar to the truck-based drone delivery problem. A notable difference between the two is that drone delivery usually uses Euclidean distance because it flies freely in the air. In contrast, robot delivery uses Manhattan distance when traveling in urban cities. Therefore, future research on the truck-based robot delivery model should consider realistic road conditions in urban cities, for example, to study how the delivery system plans the



delivery route to avoid the truck/robot “no-go” areas to achieve optimal delivery or to study how the delivery system achieves robust scheduling under uncertain traffic conditions. In addition, if trucks, robots, and drones can be combined into a distribution system to carry out multimodal transport, it may be a very promising direction (Babae Tirkolaee et al, 2024).

One noteworthy point is that existing research has seldom considered dynamic/stochastic models, which can be explored in the future—for example, truck-robot collaborative delivery systems for on-demand deliveries (Liu, 2019) or deliveries with uncertain travel time or uncertain demands (Liu et al, 2023b), or with same-day delivery scenario (Ulmer and Streng, 2019), etc.

**(2) Algorithmic perspective:** Most current problems are solved using heuristic (meta-heuristic) methods and rarely involve purely exact methods. This is because the existing research has mainly explored the potential models, which are developed to be more complex and harder to solve by exact approaches. Therefore, it seems worthwhile to summarize some basic truck-robot cooperative delivery models and apply various specific solution algorithms to the basic models, which can provide a broad range of references for other problem variants.

Machine learning approaches, especially reinforcement learning, have already been used in vehicle routing problems for almost five years, which is an innovative and promising approach (Mazyavkina et al, 2021; Hildebrandt et al, 2022). For example, using reinforcement learning to solve the problem directly and combining reinforcement learning with existing exact or heuristic algorithms have been investigated and have proven effective. Morabit et al (2021) proposed a novel method that uses a machine-learning technique to speed up column generation. This method, called column selection, applies a trained model to select a subset of the variables (columns) generated at each column generation iteration. The goal is to reduce the computational time needed for re-optimizing the restricted master problem at each iteration by choosing the most important columns. Reijnen et al (2022) introduced a deep reinforced adaptive large neighborhood search approach to tackle choosing operators for each ALNS search iteration as a sequential decision problem. The approach aims to learn from the search state which operator to use to achieve a high long-term reward. Therefore, machine-learning-related approaches can potentially be used to complement existing approaches for solving the collaborative truck-robot delivery problems.

Recent research indicates that the utilization of large language models in the optimization of heuristic algorithms can effectively enhance algorithmic efficiency (Romera-Paredes et al, 2024). Notably, these models have demonstrated commendable performance in problems such as the traveling salesman problem (Liu et al, 2023a, 2024). Consequently, we posit that the integration of heuristic algorithms with large language models could potentially present an intriguing approach to solving the collaborative truck-robot delivery problems problem.

### 5.3 Management insights

Finally, we have identified some management insights from existing studies.

From a cost perspective, existing studies have demonstrated that robot concepts are more cost-effective than a truck-only delivery solution. Robotic deliveries have

demonstrated great potential for reducing the operational costs of last-mile deliveries. Compared to traditional truck-only delivery, the truck-robot collaborative delivery concept has been shown by a significant number of articles to outperform conventional truck-only deliveries in terms of cost and service.

Ostermeier et al (2022) compared a truck-based robot (STR) model with the traditional truck-only delivery model. They estimated that using ten robots can achieve savings of 59% to 68% and reduce the distance traveled by trucks by 82%. This results in a lower cost at the first delivery level. Moreover, the results indicate that, even with much higher robot costs, the truck and robot concept allows distribution with costs below the traditional truck-only concept's lower bound. Even if the prime rate is quadrupled, the total costs only increase by 131% and remain competitive with truck-only delivery. In addition, compared to conventional truck-only deliveries, hub-based robot delivery has demonstrated its advantages, too. Bakach et al (2021) demonstrated that this concept provides a savings of 67.9% to 92.3% (from 2 to 13 hubs). Furthermore, it represents a significant cost reduction for delivery companies, as they can operate at about 24-32% of the cost of traditional truck-only deliveries with sufficient customer density. Hub-based robot delivery is most attractive when the demand for slots is unevenly distributed. Therefore, compared to the different delivery methods, hub-based robot deliveries and truck-based robot deliveries offer significant savings compared with conventional truck-only deliveries.

From a service time perspective, all options enable robot deliveries to meet tight deadlines with minimal additional cost. Ostermeier et al (2022) showed that the truck-based robot delivery approach remarkably reduces the lateness per customer by 68%, although the number of delays increases by 27%. This is because, by tolerating smaller delays for a few more customers, the truck-robot configuration can adjust its solution to minimize the total completion time and, thus, lower the total costs. In contrast, an average of three trucks are required to serve all customers in the truck-only delivery case, while one truck is enough in the truck and robot scenario. Since the truck travels a greater distance, which reduces robot travel time and delays, even with higher robot costs, the lateness is considerably reduced by 9%.

From the perspective of the applicability of the new technology, automated delivery vehicles (robots or drones) can be utilized in a complementary manner in different scenarios to reduce costs or travel distance. For instance, drones are suitable for rapid delivery in low-density areas, while robots are suitable for intensive delivery in high-density areas. Automated delivery vehicles can enhance the efficiency and flexibility of distribution to meet customers' demands for more and faster deliveries. Simultaneously, they can also lower labor costs and environmental pollution (Jennings and Figliozzi, 2020).

Similar to drone adoption (Ali et al, 2024), we expect the successful introduction of autonomous delivery robots will require concentrating on key determinants such as cost, competition, trading partners' advantage, and top management as strong supporters of the adoption.

## 6 Concluding remarks

Robot-based logistics distribution has become one of the key aspects of the intelligent transformation of logistics enterprises, as it can significantly alter their distribution modes. However, robots face limitations such as driving speed, driving distance, and load capacity, making it difficult to accomplish medium and long-distance logistics distribution independently. Meanwhile, due to their large size, traditional trucks cannot access areas such as streets. Therefore, researchers and companies have begun exploring a novel truck-robot collaborative distribution model. By leveraging the cooperation of trucks and robots to complete tasks, this model can effectively overcome their respective drawbacks, enhance the flexibility of the distribution system, and, ultimately, improve distribution efficiency.

In this paper, we have reviewed the collaborative truck-robot delivery problem. We first discussed the technical details, applications, and challenges of robot and truck-robot collaborative deliveries. Robot deliveries have been applied in various domains, such as food and beverage delivery and medical services delivery. Hub-based robot deliveries have been applied in retail and e-commerce, postal services, and mail delivery. They can improve efficiency, reduce costs, reduce environmental impacts, and enhance brand image. However, they also face challenges in the legal, infrastructural, public acceptance, and profitability aspects. We then focused on the two main models of robot delivery: hub-based and truck-based. We introduced the basic hub-based and truck-based robot delivery models and presented their mathematical formulations. We also discussed the variants and objective functions of these models. We then summarized the methodology, including the exact and heuristic methods, for solving the truck-robot delivery problem, which involves coordinating and synchronizing the movements of trucks and robots. Finally, we discussed practical aspects, model and solution approaches, as well as management insights gained throughout this study. Based on these results and discussions, we propose the following roadmap for future research on robot-based logistics:

1. **Real-World Empirical Studies:** Empirical research based on real-world data to assess the practicality and efficacy of various robot delivery models in various application scenarios. This step is crucial for understanding the viability and impact of robotics in logistics.
2. **Development of Comprehensive Models:** Crafting detailed and realistic mathematical models that accurately reflect the intricate dynamics among delivery trucks, robots, and other critical aspects like traffic conditions, consumer preferences, demand volatility, cost factors, and environmental aspects. This aims to provide a solid foundation for addressing the complexities of robot-based delivery systems to achieve sustainable last-mile delivery solutions.
3. **Combining Optimization and Machine Learning:** Designing advanced and efficient algorithms for solving complex instances of truck-robot delivery challenges within acceptable time frames, specifically leveraging machine learning techniques. This approach seeks to optimize logistical operations and enhance decision-making processes.

In advancing these research directions, the goal is to improve both the understanding and implementation of robot-based logistics significantly. This will, in turn, deliver essential insights for stakeholders in urban development and transport management, ensuring that future strategies are grounded in robust data, simulations, and real-world trials. Ultimately, this integrated approach will pave the way for innovative and practical solutions in the realm of last-mile delivery services.

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## Declarations

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