SUPPLY CHAIN AND SUSTAINABILITY RESEARCH: SCSR
VOL.4, NO.2; JUL. – DEC. ; 2025, ISSN 2822-0412 (Online)

Vehicle-Drone Collaborative Delivery: A Systematic Literature Review and Future Research Agenda

Xinyu Fan[1], Yantong Jin[1], Shi Peter[2], Nyoman Pujawan[3], Gang Wu[4], Fang Xu[4], Chaozhe Jiang[5*]

[1,4]Southwest Jiaotong University, Chengdu, China
West High-tech Zone, Chengdu, Sichuan, China
[2]Macquarie University, Sydney, Australia
123 Pitt Street, Sydney NSW, Australia
[3]Universitas Logistik dan Bisnis Internasional, Bandung, Indonesia
54, Sarijadi, Kecamatan Sukasari, Kota Bandung, Jawa Barat, Indonesia
[5] University of Waterloo, Waterloo, Canada
200 University Avenue West Waterloo, Ontario, N2L 3G1, Canada

*Corresponding author, Email: jiangchaozhe@swjtu.edu.cn

Received: Sep 10, 2025 / Revised: Dec 18, 2025 / Accepted: Dec 18, 2025

Abstract

The rise of the low-altitude economy and advances in intelligent technologies have accelerated innovation in last-mile logistics, where Vehicle-Drone Collaborative Delivery (VDCD) has become a promising solution. We systematically review 3,300+ publications and apply VOSviewer-based bibliometric analysis to synthesize research on VDCD. A four-part analytical framework is developed, covering collaboration modes, optimization objectives, problem models, and solution algorithms. The results identify four paradigms of collaboration: synchronous vehicle-drone delivery, parallel delivery, vehicle-supported drone delivery, and drone-supported vehicle delivery. Research objectives have evolved from single goals such as minimizing cost or time toward multidimensional objectives, including service coverage, customer satisfaction, and carbon reduction. Three evolutionary paths in problem modeling are observed-basic formulations, constraint-extended models, and joint optimization models-reflecting growing complexity and cross-layer integration. Algorithmic approaches fall into three main streams: exact methods, heuristics, and metaheuristics, with emerging trends in hybridization, distributed mechanisms, and adaptive strategies. Finally, this paper outlines potential directions for optimizing VDCD systems through technological innovation, policy support, and scenario-specific design, providing valuable insights for future research and practical implementation.

Keywords: Vehicle–Drone Collaborative Delivery; Path Planning; Multi-Agent Systems; Logistics Optimization; Intelligent Logistics

SUPPLY CHAIN AND SUSTAINABILITY RESEARCH: SCSR
VOL.4, NO.2; JUL. – DEC. ; 2025, ISSN 2822-0412 (Online)

การจัดส่งสินค้าร่วมกันระหว่างยานพาหนะและโดรน: การทบทวนวรรณกรรมอย่างเป็นระบบและวาระการวิจัยในอนาคต

ซินหยู่ ฟาน[1], หยานทง จิน[1], ชิ ปีเตอร์[2], นโยมาน ปูจาวัน[3]
แก๊ง หวู่[4], ฟาง ซู[4], เฉาเจ๋อ เจียง[5*]

[1,4]มหาวิทยาลัยเจียวทงภาคตะวันตกเฉียงใต้ เฉิงตู, สาธารณรัฐประชาชนจีน
เขตไฮเทคตะวันตก เฉิงตู เสฉวน, สาธารณรัฐประชาชนจีน
[2]มหาวิทยาลัยแมคควอรี, ซิดนีย์, ออสเตรเลีย
123 ถนนพิตต์, ซิดนีย์ NSW, ออสเตรเลีย
[3]มหาวิทยาลัยโลจิสติกส์และธุรกิจนานาชาติ, บันดุง, อินโดนีเซีย
54, ซารีจาดี เขตซูกาซารี เมืองบันดุง จังหวัดชวาตะวันตก, อินโดนีเซีย
[5*]มหาวิทยาลัยวอเตอร์ลู วอเตอร์ลู แคนาดา
200 ถนนยูนิเวอร์ซิตี อเวนิว เวสต์ เมืองวอเตอร์ลู, ออนแทรีโอ, N2L 3G1, แคนาดา

*(ผู้ประสานงานเผยแพร่) Corresponding author, Email: jiangchaozhe@swjtu.edu.cn

บทคัดย่อ

การเติบโตของเศรษฐกิจระดับต่ำและความก้าวหน้าของเทคโนโลยีอัจฉริยะเร่งรัดนวัตกรรมในด้านโลจิสติกส์ระยะสุดท้าย ซึ่งการจัดส่งสินค้าร่วมกันระหว่างยานพาหนะและโดรน (VDCD) นั้นกลายเป็นการแก้ปัญหาที่มีแนวโน้มดี ทบทวนสิ่งพิมพ์กว่า 3,300 ฉบับอย่างเป็นระบบ และวิเคราะห์บรรณานุกรมด้วยโปรแกรม VOSviewer เพื่อสังเคราะห์งานวิจัยเกี่ยวกับ VDCD มีการพัฒนากรอบการวิเคราะห์สี่ส่วน ครอบคลุมรูปแบบการทำงานร่วมกัน วัตถุประสงค์การเพิ่มประสิทธิภาพ โมเดลปัญหา และอัลกอริทึมในการแก้ปัญหา ผลลัพธ์ระบุกระบวนทัศน์สี่ประการของการทำงานร่วมกัน ได้แก่ การจัดส่งแบบซิงโครนัสระหว่างยานพาหนะโดรนการจัดส่งแบบคู่ขนาน การจัดส่งโดยมีโดรนสนับสนุนยานพาหนะ และการจัดส่งโดยมียานพาหนะสนับสนุนโดรน วัตถุประสงค์ของการวิจัยได้พัฒนาจากเป้าหมายเดียว เช่น การลดต้นทุนหรือเวลา ไปสู่วัตถุประสงค์หลายมิติ ซึ่งรวมถึงการครอบคลุมการให้บริการ ความพึงพอใจของลูกค้า และการลดคาร์บอนมีการสังเกตเส้นทางการพัฒนาสามประการในการสร้างแบบจำลองปัญหา ได้แก่ สูตรพื้นฐานโมเดลที่ขยายข้อจำกัดและโมเดลการเพิ่มประสิทธิภาพร่วม ซึ่งสะท้อนถึงความซับซ้อนที่เพิ่มขึ้นและการบูรณาการข้ามชั้นแนวทางด้านอัลกอริทึมแบ่งออกเป็นสามกระแสหลัก ได้แก่ วิธีการที่แม่นยำ ฮิวริสติก และเมตาฮิวริสติก โดยมีแนวโน้มที่เกิดขึ้นใหม่ในด้านการผสมผสาน กลไกแบบกระจาย และกลยุทธ์แบบปรับตัว สุดท้ายบทความนี้นำเสนอทิศทางที่เป็นไปได้สำหรับการเพิ่มประสิทธิภาพระบบ VDCD ผ่านนวัตกรรมทางเทคโนโลยี การสนับสนุนด้านนโยบาย และการออกแบบเฉพาะสถานการณ์ (Scenario-Specific Design) ซึ่งให้ข้อมูลเชิงลึกที่มีคุณค่าสำหรับงานวิจัยในอนาคตและการนำไปปฏิบัติจริง

คำสำคัญ: การจัดส่งสินค้าร่วมกันระหว่างยานพาหนะและโดรน, การวางแผนเส้นทาง, ระบบหลายตัวแทน, การเพิ่มประสิทธิภาพโลจิสติกส์, โลจิสติกส์อัจฉริยะ

Introduction

The global logistics system is facing unprecedented efficiency bottlenecks and transformation pressures. According to the World Bank, logistics costs account for more than 12% of global GDP, with last-mile delivery costs representing 28–35%. This has become a major constraint on overall supply chain efficiency (Park et al., 2023). The traditional delivery model dominated by fuel-powered vehicles faces multiple challenges. Geographic constraints reduce accessibility in remote areas and disaster response scenarios (Dorling et al., 2017). Meanwhile, the rapid growth of e-commerce has led to a surge in parcel volumes. This increase has further raised the frequency of urban delivery vehicle operations, intensifying both traffic congestion and emissions. Urban logistics vehicles alone contribute about 30% of traffic congestion and 18% of greenhouse gas emissions (Joselow, 2020).

In recent years, with breakthroughs in drone technology and the expansion of application scenarios, research on drone-based logistics delivery has developed rapidly. In 2013, Amazon first announced its drone delivery project and declared that it would enter the stage of practical application by 2017 (Rose, 2013). Soon after Google's GoogleX laboratory launched its Project Wing in 2014 (Stewart, 2014). That same year, the German company DHL successfully tested a drone delivering medicine to a small island inaccessible by truck (Bryan, 2014). However, as applications deepened, the limitations of drones such as low payload capacity and limited endurance became evident. To date, companies including Google, Amazon, DHL, and SF Express have employed drones in delivery operations. Most operate at speeds of 48–64 km/h, with ranges of 16–48 km, and a payload capacity of five kg (Heath, 2015). As a result, when logistics demand and delivery radius expand significantly, the capacity and range constraints of drone systems lead to rising marginal costs and diminishing utility, thus presenting a clear feature of diseconomies of scale.

In summary, VDCD has emerged as a promising paradigm to overcome the efficiency bottlenecks of last-mile logistics, leveraging the complementary strengths of aerial and ground transportation. While existing research has made substantial progress in model design, algorithm development, and scenario exploration, a systematic and integrative perspective is still needed to clarify the evolution path, optimization logic, and future research directions of VDCD. It should be noted that this review did not consider airspace regulation papers outside logistics journals, which may limit the breadth of policy-related insights. To address this gap, this paper provides a comprehensive review and structured analysis. The explicit contributions of this study are as follows:

Comprehensive Framework: We analyze 3,300+ publications and use VOS viewer-based bibliometric to build an integrated framework that links collaborative modes, optimization objectives, problem models, and solution algorithms.

Refined Mode Classification: We categorize VDCD into four representative paradigms and analyze their mechanisms, applications, and performance trade-offs.

Modeling and Optimization Insights: The evolution from basic to constraint-extended and joint optimization models, highlighting the shift from spatial flexibility to cross-layer resource integration, and summarize multi-objective optimization approaches beyond time and cost.

Literature Review

Sources of Literature

This study searched in the Web of Science Core Collection, including the SCI-EXPANDED and SSCI databases. The search was performed using the topic terms ‘UAV” AND “Optimization” AND “vehicle-UAV”. After a strict screening process, conference papers, review articles, and retracted publications were excluded. A total of more than 3,300 journal articles published between 2015 and the first half of 2025 were identified as relevant to the research topic. The results are shown in Figure 1

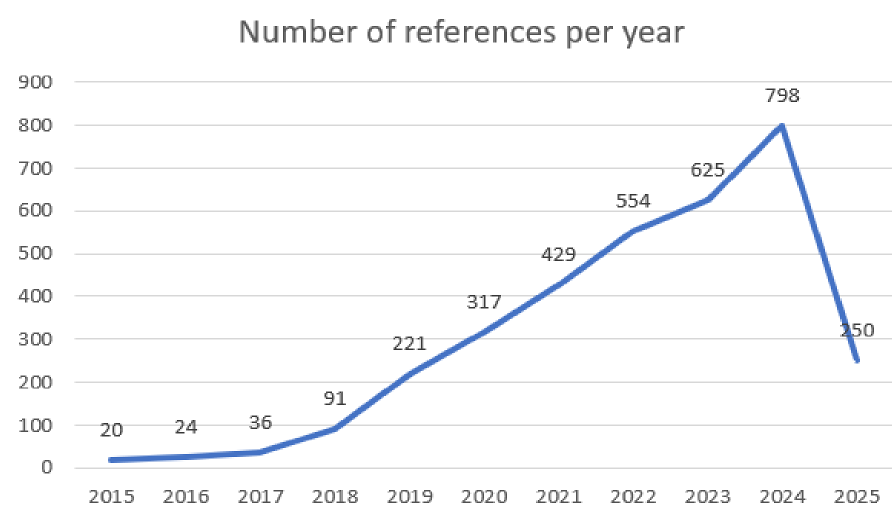

Figure 1 Annual number of published papers

The journal sources mainly include Transportation Research Record, Transportation Research Part A/B/C/D/E, IEEE Transactions on Intelligent Transportation Systems, Transportation Science, IEEE Transactions on Wireless Communications, and IET Intelligent Transport Systems. The research fields cover multiple areas, such as Engineering, Telecommunications, Computer Science, Transportation, Remote Sensing, and Instruments and Instrumentation.

This study employs VOSviewer to conduct bibliometric analysis. The software is based on co-occurrence networks and clustering techniques, which automatically extract and normalize keywords from the literature. It then generates clustering maps according to co-occurrence strength, thereby objectively revealing the structural patterns of research topics. In this analysis, only author-provided keywords were included. The minimum occurrence threshold was set to nine. Out of 8,040 keywords, 287 met this criterion. The top fifteen keywords were autonomous aerial vehicles, optimization, unmanned aerial vehicles, resource management, trajectory optimization, task analysis, wireless communication, internet of things, resource allocation, energy consumption, path planning, energy efficiency, NOMA, trajectory design, and relays. The results are shown in Figure 2 and Figure 3

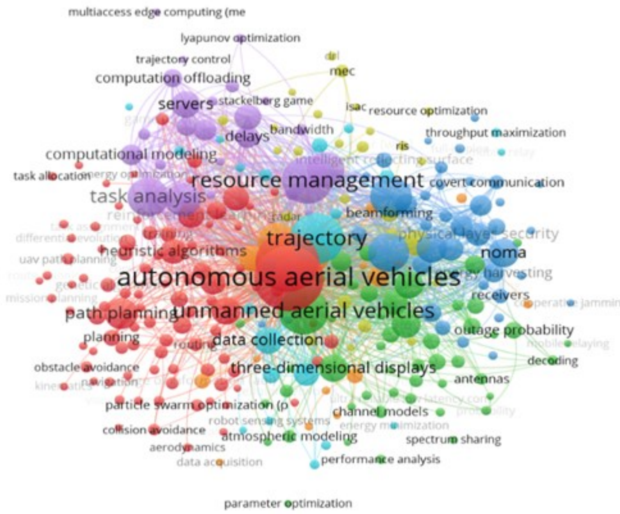

Figure 2 Keyword co-occurrence network

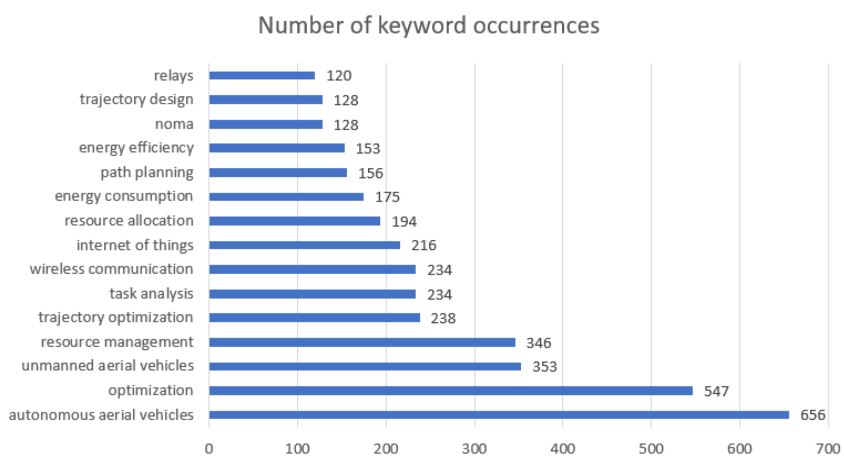

Figure 3 Top fifteen most frequently used keywords

As shown in Figures 2 and 3, the clusters centered on the thematic keyword vehicle-drone collaboration mainly include terms such as optimization, task analysis, resource allocation, and path planning. This indicates that these keywords represent the core research focuses in this field.

Problem Modeling

Vehicle-drone combined delivery can adopt multiple modes. Both vehicles and drones can participate in deliveries, or one may perform delivery while the other provides support. Based on the different roles of vehicles and drones in the collaborative delivery process, this study, following Otto et al. (2018) and Rojas et al. (2021), categorizes the problem into four types: synchronous delivery by drones and vehicles, parallel delivery by vehicles and drones, vehicle-supported drone delivery, and drone-supported vehicle delivery.

synchronous delivery by drones and vehicles

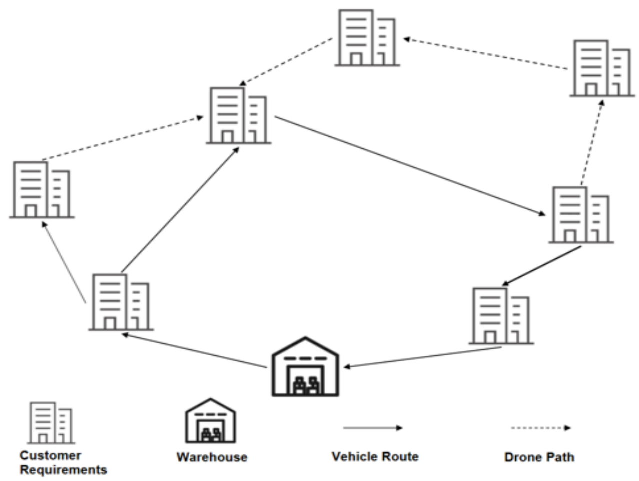

Figure. 4 Diagram of synchronized drone and vehicle delivery operation mode

The vehicle–drone collaborative delivery model is illustrated in Figure 4. In this mode, the vehicle and drones serve their respective customer nodes, with the vehicle carrying one or more drones. Research in this area focuses on the coordinated optimization of vehicle and drone path planning and task execution. The aim is to address drone endurance limitations, spatiotemporal synchronization requirements, and road constraints, while optimizing multiple objectives such as cost, time efficiency, energy consumption, and service coverage. Typically, the vehicle serves as a mobile platform or resupply point for drones. Modeling studies consider scenarios of varying complexity. In basic scenarios, vehicles follow predefined routes while drones take off from the vehicle to serve one or multiple customers before returning. The vehicle must wait at designated times and locations for drone rendezvous. To improve efficiency and coverage, models have evolved. Teimoury et al. (2024) introduced non-customer rendezvous locations, allowing vehicles to meet drones at points other than customer nodes, greatly increasing path planning flexibility. The mobile resupply mode was proposed to overcome fixed stop limitations. While the vehicle moves along roads, drones can take off, land, and receive battery or cargo replenishment, significantly extending service range and continuity (Maini et al., 2019; Gu et al., 2023). Energy management strategies have also been incorporated. Yurek et al. (2021) explored dynamic charging as an alternative to battery replacement to better reflect practical scenarios and reduce downtime. In complex scenarios, multi-objective delivery is considered. Teimoury et al. (2024) allowed drones to visit multiple customers in a single flight. Gu et al. (2023) addressed dynamic demand, requiring models to efficiently update paths in response to real-time delivery requests.

Research has thoroughly demonstrated the significant advantages of the synchronous delivery mode in improving last-mile logistics efficiency. The core of this mode lies in leveraging the collaborative effects at the last-mile stage. Drones can efficiently handle small-batch, multi-trip, and geographically dispersed delivery tasks, effectively compensating for the limitations of ground vehicles in complex road conditions, remote areas, and emergency demand scenarios. Vehicles, in turn, manage mainline transportation and bulk deliveries, achieving complementary use of aerial and ground resources. Integrating drones into the delivery system can reduce last-mile delivery time, minimize vehicle idling and waiting, and enhance system flexibility and robustness while maintaining overall operational stability. An empirical study by Gu et al. (2023) shows that using a single-vehicle, single-drone mobile base station in dynamic scenarios can increase service efficiency by 50% and raise operational profit by 15%, further confirming the feasibility and value of this collaborative delivery mode.

parallel delivery by vehicles and drones

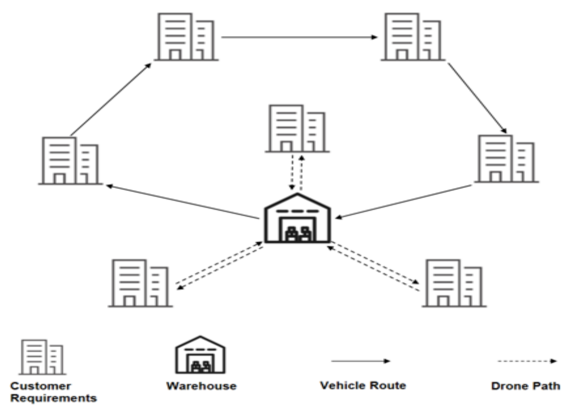

Figure. 5 Diagram of vehicle and drone parallel delivery operation mode

Parallel delivery by vehicles and drones refers to a mode in which both participate in the same delivery task but operate as independent transport units, performing their respective tasks without interference. The operational scheme is illustrated in Figure 5. In this mode, drones depart directly from the distribution center and return, serving nearby customers in a point-to-point manner. Vehicles, on the other hand, carry the entire load at once and deliver to customers in more distant areas. In parallel delivery, drones only pick up items and recharge at the distribution center. There is no need for temporal or spatial coordination with vehicles, which is why this mode is referred to as parallel delivery. This mode demonstrates significant value across diverse scenarios. Edirimanne et al. (2024) used pizza delivery in Sri Lanka as an empirical setting, developing a capacity-constrained VRP drone model. Their results show that this approach outperforms traditional motorcycles and optimized motorcycle systems in terms of travel distance, time, cost, and emissions. For special-demand scenarios, Ramos et al. (2023) focused on dynamic, real-time drug delivery from rural pharmacies in Portugal. They systematically modeled a vehicle–drone collaborative mechanism under dual constraints of real-time order arrivals and strict delivery deadlines. To enhance system robustness, Wang et al. (2021) proposed a multimodal integrated architecture that coordinates truck fleets, mobile drones carried by trucks, and fixed stations multiple traveling salesman problem and location allocation problem model (mTSP-LAP), achieving efficient linkage among heterogeneous nodes. Facing large-scale logistics challenges, Shi et al. (2025) developed a multi-vehicle, multi-drone collaborative framework to address the coupled constraints of drone endurance, payload, and truck load capacity, significantly reducing system energy consumption. Kloster et al. (2023) incorporated fixed drone stations into the multi traveling salesman problem (mTSP), coordinating vehicle routing and drone task scheduling to reduce delivery time while optimizing energy usage. Nguyen et al. (2022) proposed a parallel delivery model Parallel Drone Scheduling Vehicle Routing Problem (PDSVRP) with the core objective of minimizing total operational cost, aiming to improve multiple performance dimensions.

Parallel delivery by vehicles and drones can fully leverage the flexibility of drones and the long endurance and high payload capacity of vehicles. This enables adaptation to multiple scenarios while improving system robustness and wide-area coverage. However, the mode is constrained by drone endurance and payload limits, as well as additional operational costs related to matching vehicle and drone resources and the layout of stations.

vehicle-supported drone delivery

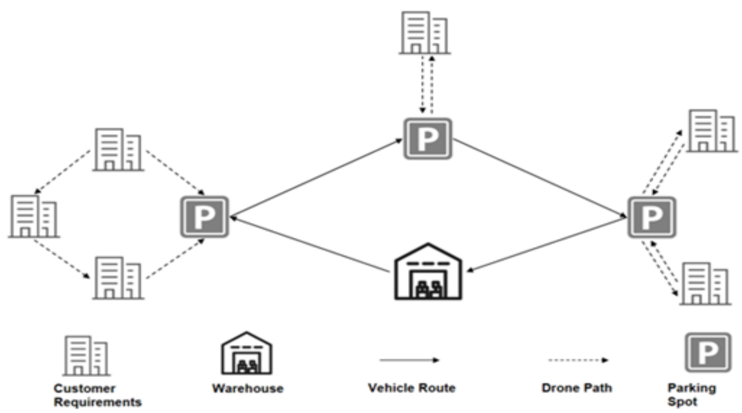

Figure 6 Vehicle secured drone delivery operation model diagram

The vehicle supported drone delivery mode is illustrated in Figure 6. In this mode, drones execute the delivery tasks while vehicles serve as supporting platforms. This mode can be implemented through multiple approaches. Vehicles may act as mobile transport platforms, carrying drones to the task area before drones complete all deliveries (Mathew et al., 2015). They can also function as mobile energy supply stations, significantly extending drone operation time through dynamic charging (Ropero et al., 2019) or vehicle–drone bidirectional energy-sharing mechanisms (Zhu et al., 2024). Vehicles can further integrate with public transportation networks to form multi-level relay hubs. For example, drones may ride on buses to reach remote transfer stations and then complete last-mile delivery using charging stations for battery replacement (Huang et al., 2022). In high-density last-mile delivery scenarios, vehicles may be upgraded to multifunctional mobile bases, serving as cargo storage, take-off/landing platforms, and charging stations to support multiple rounds of drone pick-up and delivery (Mulumba et al., 2024).Meng et al. (2023) proposed the DAPDP model, which overcomes the traditional single-visit limitation by simultaneously integrating multi-visit services, bidirectional pick-up and delivery demand, truck capacity constraints, and load-dependent energy optimization.

At the energy coordination level, Zhu et al. (2024) advanced from basic charging to dynamic energy transfer, optimizing energy utilization efficiency. In terms of coverage, Huang et al. (2022) expanded the service network using public transportation, reducing dependence on infrastructure in remote areas. Regarding operational capability, Meng et al. (2023) integrated multi-visit and synchronized pick-up and delivery requirements, enhancing practical applicability in commercial scenarios. As a result, vehicles transform from single-purpose transport units into core hubs for spatiotemporal coordination and resource sharing. They provide systematic support for drones in long-distance delivery, wide-area continuous operations, and high-density last-mile deliveries, fundamentally extending the operational boundaries and economic feasibility of drone deployment.

drone-supported vehicle delivery.

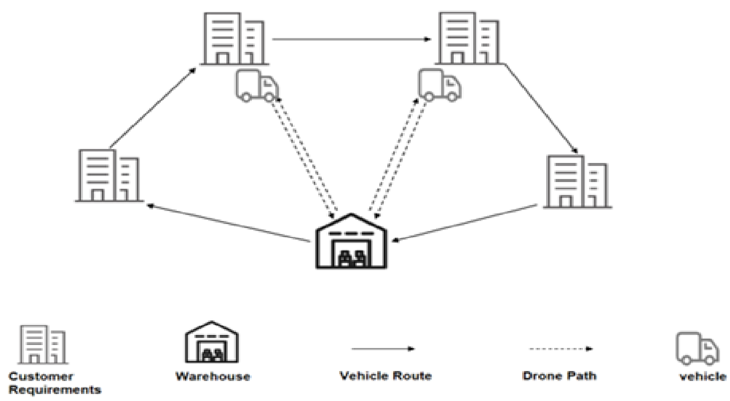

Figure 7 Drone-guaranteed vehicle delivery operation mode diagram

The drone-supported vehicle delivery mode is illustrated in Figure 7. In this mode, vehicles lead the delivery tasks while drones serve as auxiliary tools for cargo replenishment. This mode demonstrates paradigm innovation in key scenarios. In logistics operations, Dayarian et al. (2020) defined it under the comprehensive formulation of the Vehicle Routing Problem with Drone Replenishment (VRPDR). Drones continuously pick up goods from the distribution center to provide real-time replenishment for vehicles enroute, enabling vehicles to exceed their initial load capacity and complete more deliveries within strict time windows. In urban management, Xu et al. (2023) proposed the Vehicle–Drone Collaborative Arc Routing Problem (GVD-ARP) to meet traffic patrol requirements. By leveraging drones to extend monitoring coverage while overcoming endurance constraints, this approach reduces labor costs and improves response speed to emergencies. In emergency scenarios, Gao et al. (2020) developed a spatiotemporal synchronized network integrating drones and mobile charging stations, formally termed the Vehicle Routing Problem with Spatiotemporal Synchronization Network (VRPSN). Coordinated path planning between drones and charging vehicles enhances both equipment utilization and response efficiency in post-disaster search and rescue operations.

The core advancement of such models lies in the flexible scheduling of low-altitude resources. This approach addresses inherent challenges in vehicle delivery, including cargo stock limitations, response delays, and task continuity, ultimately achieving systematic improvements in logistics efficiency, service coverage, and emergency response capability.

Optimization Objectives

The optimization objectives in vehicle–drone collaborative delivery mainly focus on two dimensions: time and cost. Some studies also consider additional factors such as delivery distance, customer satisfaction, and the number of drones.

In terms of time-related optimization objectives, although different studies adopt varying models and constraints, the most common goal remains minimizing total delivery time or the time required to complete delivery tasks. For example, Raj et al. (2020) minimized delivery time by dynamically adjusting drone flight speed. Luo et al. (2021) overcame the limitation of single-flight, single-package delivery and set total task time minimization as the optimization objective. Daknama et al. (2017) focused on minimizing the average delivery time per package. Luo et al. (2017) aimed to minimize drone flight time, while Kitjacharoenchai et al. (2019) sought to reduce the total time for all vehicles to complete tasks and return to the distribution center. A detailed analysis is as follows:

(1) Minimization of Total Delivery Time

The objective function is to minimize the total delivery and waiting time of all vehicles and drones in the system, as shown in Equation (1):

$$T_{sum} = min\left\{\sum_{i,j\in N} t_{ij}\cdot x_{ij} + \sum_{i\in N} S_i + \sum_{i,j\in N} t_{ij}\cdot y_{ij}\right\} \tag{1}$$

x_{ij}represents the delivery time from point i to j; x_{ij} and y_{ij} are binary decision variables (x_{ij} represents the drone path, and y_{ij} represents the vehicle path); S_i denotes the waiting time at node i , calculated as $S_i = |\tau_i^C - \tau_i^D|$ (the time difference between vehicle and drone arrivals).

(2) Minimization of Completion Time

The objective function is to minimize the final time for vehicles and drones to complete all delivery tasks and return to the depot. When drones can return to the depot, the maximum of vehicle and drone return times is taken, as shown in Equation (2). When drones cannot return to the depot, the maximum of the vehicle return time and the retrieval time of the last drone is taken, as shown in Equation (3):

$$T_{finish} = min\left\{max\{\tau_{n+1}^C, \tau_{n+1}^D\}\right\} \tag{2}$$

$$T_{finish} = min\left\{max\left\{\tau_{n+1}^C, \max_{k\in K} \tau_k^{recovery}\right\}\right\} \tag{3}$$

Besides time, cost minimization is also an important optimization objective. Depending on the components of cost, different studies model cost minimization in various ways. For example, Mulumba et al. (2024) studied drone-assisted pick-up and delivery problems with the goal of reducing logistics costs. Sacramento et al. (2015) demonstrated that a mobile base station mode could reduce logistics costs by up to 48% under optimal conditions. Boccia et al. (2024), focusing on improving customer satisfaction, set operational cost minimization as the optimization objective. However, cost modeling is complex and often influenced by multiple variables. This is particularly evident when nonlinear cost factors, such as fuel consumption, are involved. In practice, it is also difficult to comprehensively identify and quantify all cost components. A detailed analysis is as follows:

(3) Minimization of Variable Cost

The objective function is to minimize the operating cost associated with the delivery routes, as shown in Equation (4):

$$C_{var} = min\left\{\sum_{i,j\in N} c_{ij}\cdot\left(x_{ij}+y_{ij}\right)+\sum_{i\in N} c_w\cdot S_i\right\} \tag{4}$$

c_{ij} represents the unit distance/time cost for path (i,j), and c_w represents the unit cost of waiting time.

(4) Minimization of Fixed Cost

The objective function is to minimize the resource activation cost, as shown in Equation (5):

$$C_{fix} = min\left\{\sum_{k\in K} f_k\cdot\delta_k+\sum_{w\in W} f_w\cdot\gamma_w\right\} \tag{5}$$

δ_k, γ_w are binary variables (equal to 1 when drone k or vehicle w is used), f_k, f_w represent the fixed activation costs of the corresponding resources.

In addition, some studies have proposed other optimization directions, such as minimizing the total travel distance (Halil et al., 2015; Kim, 2018), minimizing the number of vehicles required (Han et al., 2020), maximizing the number of served customers (Ulmer et al., 2018), maximizing customer satisfaction (Budak et al., 2023; Ren et al., 2023), and minimizing carbon emissions during the delivery process (Peng et al., 2025; Zhu et al., 2024).

Problem Models

In line with the aforementioned optimization objectives, problem models have evolved from basic models to constraint-extended models and joint optimization models, showing a progressive path from expanding spatial degrees of freedom to integrating cross-layer resources.

basic models Basic models focus on overcoming spatial and task constraints. At the spatial level, Masone et al. (2022) proposed an edge launch capability framework, allowing drones to take off and land at any position on the road for the first time, while integrating battery limitations, truck waiting times, and multi-package delivery constraints. This approach removes the restrictions of fixed take-off and landing points on path planning. Salama et al. (2022) further extended this concept with a flexible launch and recovery site model, enabling trucks to launch and recover drones at preselected non-customer locations, fully decoupling take-off and landing operations from customer nodes. At the task capability level, Luo et al. (2021) overturned the "single-flight, single-package" assumption and developed a collaborative path model supporting drones to serve multiple customers in a single flight, significantly improving delivery efficiency. At the system architecture level, Stodola et al. (2024) introduced a mobile base multi-depot path model, allowing trucks to act as drone transfer stations for cross-depot resource scheduling, breaking single-depot operation boundaries. Murray et al. (2020) integrated nonlinear endurance constraints into multi-drone queue scheduling for the first time. Their automated scenario analysis revealed the diminishing marginal returns of adding drones and quantified the risks of misapplying endurance models, providing critical parameter guidance for large-scale systems.

These basic models collectively drive the evolution of collaborative delivery systems from rigid frameworks to flexible spatial paradigms. By supporting take-off and landing at arbitrary locations and operations at non-customer points, they release spatial constraints. Combined with multi-customer service and cross-depot scheduling, they reconstruct task logic. Integrating precise modeling of nonlinear drone endurance, these approaches ultimately establish a foundational framework for dynamic optimization capable of supporting complex real-world scenarios.

Constraint-Extended Models

Constraint-extended models address dynamic and uncertain environments by embedding optimization objectives within more complex constraint systems. Ren et al. (2023) proposed a mobile battery swapping mechanism, simultaneously optimizing electric vehicle routes and drone endurance strategies. This approach achieves dynamic energy coordination under time-varying traffic flows, reducing carbon emissions by 28% and promoting green "last-mile" delivery. Yin et al. (2023) addressed dual uncertainties in demand and travel time in post-disaster scenarios. They used a budgeted uncertainty set to model parameter perturbations and developed an arc-based model minimizing worst-case delay penalties, improving disaster response reliability by over 30%. Meng et al. (2024) interactively modeled multi-visit service, synchronized pick-up and delivery, truck capacity constraints, and load-dependent drone energy consumption for the first time. This filled a gap in complex commercial logistics modeling, reducing operational costs of bidirectional medical supply delivery by 19.7%. Thomas et al. (2024) proposed a joint optimization framework for heterogeneous fleets and dynamic take-off/landing points. By unifying decisions on in-transit take-off and landing operations, vehicle scheduling, and path planning, they achieved a 40-fold improvement in computational efficiency for scenarios involving hundreds of customers.

These extended models better reflect real operational contexts and can maintain time and cost optimization while simultaneously enhancing system resilience and sustainability.

joint optimization models

Joint optimization models achieve deep integration of cross-level decisions, collaboratively optimizing location, routing, and energy within a single framework. Meng et al. (2024) developed a two-level location-routing optimization framework. They improved clustering algorithms to optimize blood distribution center locations and designed intelligent algorithms for coordinated route planning. In complex road networks, this approach simultaneously reduced total cost by 12.65% and delivery time by 37.5%, providing key decision support for emergency medical services. They further proposed a UGV/UAV energy joint optimization model, integrating path planning with intelligent decision-making to systematically balance vehicle movement and flight energy consumption. Cai et al. (2023), in extreme environment patrol tasks, used an energy coordination scheduling mechanism to overcome traditional energy constraints, extending system endurance by 45% and addressing continuous operation bottlenecks in scenarios such as planetary exploration. Li et al. (2020) introduced a mobile satellite architecture, converting trucks into dynamic supply points and establishing a two-level optimization model for supply point positioning and real-time UAV path coordination. This expanded rural delivery coverage by 58% while reducing flight distance by 25.4%. Gao et al. (2023) proposed a three-level nested decision framework (customer assignment-drone scheduling-vehicle routing) for multi-vehicle multi-drone systems. Using mixed-integer programming and hierarchical solution methods, they supported optimization for hundreds of customers, reducing time-window violations in instant medicine delivery to below 4%.

These models enable balancing of timeliness, cost, coverage, and energy consumption under multi-objective optimization, providing systematic solutions for large-scale and complex constraint scenarios.

Solution Algorithms

Solution algorithms can be discussed in three main categories: exact algorithms, heuristic algorithms, and metaheuristic algorithms.

Table 1 Comparison of algorithm characteristics

Type	Representative Method	Advantages	Disadvantages
Precise Algorithm	Branch pricing method, Benders decomposition	Guarantee globally optimal solutions with rigorous theory	Only applicable to small-scale and computation-intensive scenarios.
Heuristic Algorithm	Mileage Saving Method, Neighbourhood Search	Real-time, fast (second-level), easy to handle complex constraints	Unstable quality, prone to local optimization
Metaheuristic Algorithm	Genetic algorithm (GA), Ant colony optimization (ACO)	Strong global search, approaching the optimal solution	High computational cost (hourly), requires experience-based parameter tuning

Exact algorithms

Exact algorithms in vehicle–drone collaborative optimization are primarily based on mathematical programming and decomposition strategies, constructing theoretically complete solution frameworks. Their core lies in guaranteeing optimality through structured search and cutting-plane techniques. Typical methodologies include: branch-and-bound, which solves mixed-integer programming models through systematic enumeration and pruning; branch-and-price, which dynamically handles large-scale path variables using column generation; Benders decomposition, which splits the problem into a vehicle routing master problem and a drone scheduling subproblem, iteratively optimizing via cutting planes; and dynamic programming, which optimizes decision sequences for specific substructures.

Tamke et al. (2021) designed the first branch-and-bound cutting-plane algorithm for the vehicle routing problem with drone replenishment (VRPD), dynamically identifying and adding cutting planes to strengthen linear relaxations. Cavani et al. (2021) proposed a compact MILP model combined with branch-and-cut decomposition, increasing the solvable scale from 10 to 24 customers. Yin et al. (2023) developed an enhanced branch-and-price-and-cut algorithm for time-window constrained collaborative delivery, significantly improving efficiency by combining bounded bidirectional labeling with subset row inequalities. Boccia et al. (2024) built a two-stage robust optimization model for post-disaster dual-echelon delivery, integrating column-and-constraint generation with branch-and-cut to solve worst-case collaborative plans. Faiz et al. (2024) applied column-and-constraint generation to optimize dual-echelon routes under uncertain demand.

Although these algorithms excel in theoretical completeness and small-scale problem solving, their computational complexity remains a practical limitation. Existing exact methods are generally suitable only for small instances. In practice, they are often embedded with heuristic strategies to balance solution efficiency and quality, making them more applicable for benchmark validation or high-precision small-scale scenarios.

heuristic algorithms

In vehicle–drone collaborative optimization, heuristic algorithms rapidly generate feasible solutions through customized rules, providing real-time scheduling capabilities for large-scale dynamic scenarios. Their key features include efficient handling of complex constraints, low parameter dependency, and fast convergence. Typical methods include neighborhood search, smoothed greedy algorithms, and column generation decomposition heuristics, which demonstrate significant solution advantages across diverse scenarios.

For example, Kuo et al. (2022) designed a variable neighborhood search (VNS) algorithm with a novel solution representation for time-window constrained collaborative delivery, efficiently optimizing vehicle-drone joint routes and delivery costs. Mulumba et al. (2024) proposed a Clarke-Wright savings-based heuristic for integrated pick-up and delivery scenarios to minimize operational costs. Shi et al. (2023) developed an end-to-end differentiable framework using stochastic smoothing for sub-model differentiable optimization, combined with a smoothed greedy heuristic to improve mobile charging station routing decisions. Faiz et al. (2020) developed a column generation decomposition heuristic for post-disaster uncertain demand, optimizing dual-level drone rescue route coordination.

Although heuristic algorithms excel in computational efficiency and scenario adaptability, their global search capability is limited. They are prone to local optima and cannot guarantee optimality. Therefore, in practice, they are often used as lightweight solvers for medium-scale problems or combined with metaheuristic algorithms to form hybrid strategies, balancing real-time requirements and solution quality, and supporting robust collaborative decision-making in dynamic environments.

Metaheuristic algorithms

In the field of vehicle–drone collaborative optimization, metaheuristic algorithms use global search mechanisms inspired by natural phenomena, such as population evolution and pheromone transmission, to balance exploration and exploitation in the solution space. They are the preferred approach for large-scale, multi-node, and complex scenarios. Their main advantages include strong generality, flexible integration of problem features (e.g., encoding endurance constraints), guaranteed feasibility of solutions (sacrificing optimality compared with exact algorithms), and superior global search capability compared with heuristic methods. Typical algorithms include ant colony optimization (ACO), genetic algorithms (GA), artificial bee colony (ABC), and their hybrid strategies. Recent research shows three main capabilities: Robustness enhancement via hybrid strategies, Ghaffar et al. (2024) combined simulated annealing with ABC to overcome local optimal stagnation in medical supply delivery; Ming et al. (2019) integrated GA with an adaptive max–min ACO system (GA-AMMAS) to improve route quality under real-time traffic; Konstantinos et al. (2025) nested GA within a robust optimization framework to resist uncertainty disturbances.

Adaptive mechanisms for practical application, Deng et al. (2022) integrated improved K-means with ACO to perform load- and energy-sensitive task–path joint optimization; Stodola et al. (2023) designed an adaptive ACO with node clustering (AACO-NC), enhancing complex scenario performance through dispatch probabilities and local search.

Multi-objective collaborative optimization, Gu et al. (2023) developed a multi-level pheromone mechanism to improve ACO for real-time delivery link optimization; Li et al. (2020) used GA to balance cost and carbon emission in green delivery; Sadok et al. (2024) proposed a distributed GA-based clustering algorithm for coordinated scheduling of vehicles and drones under load and energy constraints.

These algorithms, through bio-inspired simulation and hybrid strategy innovations, establish efficient search paradigms in high-dimensional solution spaces for logistics scheduling, emergency response, and green delivery. They provide scalable technical pathways for ultra-large-scale collaborative optimization.

Table 2 Typical techniques and evolutionary directions of meta-heuristic algorithms

Typical Technology	Authors	Application Scenarios	Areas for Improvement
GA + ACO ACO+Simulated Annealing Genetic Algorithm + Robust Optimization	Ghaffar et al. (2024)	Emergency delivery of medical supplies.	Enhance global search capabilities by introducing perturbation mechanisms through simulated annealing and strengthen solution stability under emergency tasks.
	Ming et al. (2019)	Dynamic route planning under real-time traffic changes	Introducing an adaptive pheromone adjustment mechanism to improve path solution quality and convergence speed in dynamic environments
	Konstantinos et al. (2025)	High uncertainty task scheduling and path reconstruction.	Introducing genetic operators into robust optimization to improve solution feasibility and robustness under demand and traffic uncertainty
Supply Chain Risk Management	Deng et al. (2022)	Multi-vehicle-multi-drone coordinated dispatching.	Utilizing K-means clustering to reduce search scale, introducing load and energy consumption coding to enhance energy efficiency optimization capabilities.
	Stodola et al. (2023)	Large-scale, multi-task, multi-constraint complex path planning.	Combining node clustering and adaptive pheromone updating to improve search efficiency and stability under multiple tasks and complex constraints.
Supply Chain Inventory Management	Gu et al. (2023)	Real-time delivery network optimization.	Balancing the search intensity of different objectives through a multi-level pheromone mechanism to achieve solution set diversity for multi-performance optimization.
	Li et al. (2020)	Green logistics and carbon emission control.	Introducing multi-objective fitness functions into genetic algorithms to optimize the Pareto frontier quality of cost and carbon emissions
	Sadok et al. (2024)	Joint scheduling of vehicles and drones under load-energy consumption coupling.	Embedding genetic clustering into a distributed framework to improve computational efficiency and scalability under large-scale multi-constraint conditions.

Conclusion

This paper synthesizes the development of VDCD across four dimensions: collaborative modes, optimization objectives, problem models, and solution algorithms. Four paradigms—synchronized delivery, parallel delivery, vehicle-supported drone delivery, and drone-supported vehicle delivery—demonstrate distinct operational mechanisms and application scenarios. Research has shifted from single objectives, such as minimizing time and cost, toward multi-dimensional goals that incorporate service quality, sustainability, and carbon reduction. Problem modeling has advanced from basic formulations to joint optimization frameworks, reflecting a growing emphasis on resource integration. Solution methods show a progression from exact algorithms for small-scale tasks to heuristic and metaheuristic approaches for complex environments, with hybrid and distributed optimization emerging as promising trends. For managers, these findings suggest the importance of selecting collaborative modes suited to specific contexts and adopting multi-criteria decision frameworks supported by AI-based tools. For policymakers, the results highlight the need for clear regulations on airspace management, data sharing, and green logistics incentives. Nevertheless, current studies remain limited by reliance on simulations and idealized assumptions, with few empirical validations in real-world settings.

Future Research Agenda for VDCD

Building on the identified challenges of VDCD development, namely adaptation to dynamic environments, green sustainability, cross-level optimization, and large-scale implementation, future research can be advanced across the following key dimensions:

Real-time optimization under dynamic and uncertain environments

Collaborative decision-making frameworks for vehicles and drones should deeply integrate traffic flow, order demand, and weather forecasts with route planning. This enables second-level decision updates, improves service stability during peak periods and unexpected scenarios, and has direct applications in instant delivery and public service distribution.

Full-chain carbon quantification and green optimization strategies

Life-cycle carbon emission models covering energy production, transportation, and charging should be developed, with low-carbon and sustainability goals as core optimization objectives. On this basis, the collaborative effects of drones' zero-emission operation and trucks' new-energy fuel innovations can be studied in task allocation, route planning, and energy supply strategies. Carbon budget or trading constraints can be used to significantly reduce system-wide emissions, promoting standardized and commercial applications of low-carbon collaborative delivery.

Cross-level joint optimization for large-scale logistics networks

For large node scales, diverse task types, and strict real-time requirements, scalable frameworks combining hierarchical partitioning and cloud–edge collaborative computing should be proposed. These frameworks can simultaneously optimize site selection, routing, scheduling, and energy supply, maintaining computational feasibility and reducing scheduling delays in high-dimensional decision spaces.

Policy–technology integrated pathways for large-scale deployment

Simulation-policy collaborative evaluation platforms should be established to assess the safety and economic performance of airspace opening policies, take-off/landing site layouts, and operational modes. This provides quantitative support for hierarchical airspace management and safety certification standards, facilitating the commercialization and large-scale operation of VDCD.

High-reliability safety and fault-tolerance mechanisms

Task migration and redundancy allocation mechanisms should be introduced to enable seamless task takeover in cases of drone failure, communication interruption, or vehicle delay. Blockchain or multi-signature mechanisms can ensure tamper-proof scheduling data, enhancing usability in high-safety scenarios such as medical or emergency material delivery.

In summary, vehicle and drone collaborative delivery represents a vital technological pathway for smart logistics and the low-altitude economy. Future research should emphasize the integration of technology and policy, as well as algorithms and applications, to develop a multi-agent collaborative delivery system that achieves economic efficiency, environmental sustainability, and operational safety. Such efforts will drive the large-scale and sustainable advancement of VDCD within global smart logistics networks.

Declaration of competing interest

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

References

Park, S., Setiawan, E. B., Abidin, Z., & Ricardianto, P. (2023). The impact of the logistics performance index on global trade volume between the republic of Korea and major GVC reconfiguration participants in ASEAN. *Decision Science Letters, 12*(4), 671-684.

Dorling, K., Heinrichs, J., Messier, G. G., & Magierowski, S. (2017). Vehicle routing problems for drone delivery. *IEEE Transactions on Systems Man Cybernetics-Systems, 47*(1), 70-85.

Joselow, M. (2020). Delivery vehicles increasingly choke cities with pollution. *Scientific American*. Retrieved November 30, 2022.

Rose, C. (2013). Amazon's Jeff Bezos looks to the future. *CBS News*, 1.

Stewart, J. (2014). Google tests drone deliveries in project wing trials. *BBC World Service Radio*.

Bryan, V. (2014). Drone delivery: DHL'parcelcopter'flies to German isle. *Reuters*, 24.

Heath, N. (2015, October). The long-range drone that can keep up with a car and fly for an hour.

Otto, A., Agatz, N.,Campbell, J.,Golden, B. & Pesch, E. (2018). (Optimization approaches for civil applications of unmanned aerial vehicles (UAVs) or aerial drones: A survey). *NETWORKS,72*(4),411-458

Rojas Viloria, D., Solano-Charris, E. L.,Munoz-Villamizar, A., & Montoya-Torres, J. R. (2021). (Unmanned aerial vehicles/drones in vehicle routing problems: a literature review). *INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH,28*(4),1626-1657

Teimoury, E. & Rashid, R. (2024). (A hybrid variable neighborhood search heuristic for the sustainable time-dependent truck-drone routing problem with rendezvous locations). J*OURNAL OF HEURISTICS,30*(1-2),1-41

Gao, W., Luo, J., Zhang, W., Yuan, W., & Liao, Z. (2020). Commanding Cooperative UGV-UAV With Nested Vehicle Routing for Emergency Resource Delivery. *IEEE Access, 8*, 215691-215704.

Maini, P., Sundar, K., Singh, M., Rathinam, S., & Sujit, P. B. (2019). Cooperative Aerial-Ground Vehicle Route Planning With Fuel Constraints for Coverage Applications. *IEEE Transactions on Aerospace and Electronic Systems, 55*(6), 3016-3028.

Gu, R., Liu, Y., & Poon, M. (2023). Dynamic truck-drone routing problem for scheduled deliveries and on-demand pickups with time-related constraints. *Transportation Research Part C-Emerging Technologies, 151*(1).

Yurek, E. E., & Ozmutlu, H. C. (2021). Traveling salesman problem with drone under recharging policy. *Computer Communications, 179*, 35-49.

Edirimanne, R., Fernando, W. M., Nielsen, P., Niles Perera, H., & Thibbotuwawa, A. (2024). Optimizing unmanned aerial vehicle for food delivery through vehicle routing problem: A comparative analysis of three delivery systems. *Applied Computer Science, 20*(1), 85-105.

Ramos, T. R. P., & Vigo, D. (2023). A new hybrid distribution paradigm: Integrating drones in medicines delivery. *Expert Systems with Applications, 234*(1).

Wang, C., Lan, H., Saldanha-da-Gama, F., & Chen, Y. (2021). On Optimizing a Multi-Mode Last-Mile Parcel Delivery System with Vans, Truck and Drone. *Electronics, 10*(20), Article 2510.

Shi, X., Zhai, X., Wang, R., Le, Y., Fu, S., & Liu, N. (2025). Task Planning of Multiple Unmanned Aerial Vehicles Based on Minimum Cost and Maximum Flow. *Sensors, 25*(5), Article 1605.

Nguyen, M. A., Dang, G. T. H., Ha, M. H., & Pham, M. T. (2022). The min-cost parallel drone scheduling vehicle routing problem. *European Journal of Operational Research, 299*(3), 910-930.

Kloster, K., Moeini, M., Vigo, D., & Wendt, O. (2023). The multiple traveling salesman problem in presence of drone- and robot-supported packet stations. *European Journal of Operational Research, 305*(2), 630-643.

Mathew, N., Smith, S. L., & Waslander, S. L. (2015). Planning Paths for Package Delivery in Heterogeneous Multirobot Teams. *IEEE Transactions on Automation Science and Engineering, 12*(4), 1298-1308.

Ropero, F., Munoz, P., & R-Moreno, M. D. (2019). TERRA: A path planning algorithm for cooperative UGV-UAV exploration. *Engineering Applications of Artificial Intelligence, 78*, 260-272.

Huang, H., & Savkin, A. V. (2022). Deployment of Charging Stations for Drone Delivery Assisted by Public Transportation Vehicles. *IEEE Transactions on Intelligent Transportation Systems, 23*(9), 15043-15054.

Zhu, T., Boyles, S. D., & Unnikrishnan, A. (2024). Battery Electric Vehicle Traveling Salesman Problem with Drone. *Networks & Spatial Economics, 24*(1), 49-97.

Meng, S., Guo, X., Li, D., & Liu, G. (2023). The multi-visit drone routing problem for pickup and delivery services. *Transportation Research Part E-Logistics and Transportation Review, 169*.

Mulumba, T., Najy, W., & Diabat, A. (2024). The drone-assisted pickup and delivery problem: An adaptive large neighborhood search metaheuristic. *Computers & Operations Research, 161*.

Dayarian, I., Savelsbergh, M., & Clarke, J. P. (2020). Same-Day Delivery with Drone Resupply. *Transportation Science, 54*(1), 229-249.

Xu, B., Zhao, K., Luo, Q., Wu, G., & Pedrycz, W. (2023). A GV-drone arc routing approach for urban traffic patrol by coordinating a ground vehicle and multiple drones. *Swarm and Evolutionary Computation, 77*.

Raj, R., & Murray, C. (2020). The multiple flying sidekicks traveling salesman problem with variable drone speeds. *Transportation Research Part C-Emerging Technologies, 120*, Article 102813.

Luo, Z., Poon, M., Zhang, Z., Liu, Z., & Lim, A. (2021). The Multi-visit Traveling Salesman Problem with Multi-Drones. *Transportation Research Part C-Emerging Technologies, 128*, Article 103172.

Daknama, R., & Kraus, E. (2017). Vehicle routing with drones. *arXiv.*

Boccia, M., Masone, A., Sforza, A., & Sterle, C. (2021). A column-and-row generation approach for the flying sidekick travelling salesman problem. *Transportation Research Part C-Emerging Technologies, 124*, Article 102913.

Luo, Z., Liu, Z., & Shi, J. (2017). A Two-Echelon Cooperated Routing Problem for a Ground Vehicle and Its Carried Unmanned Aerial Vehicle. *Sensors, 17*(5), Article 1144.

Kitjacharoenchai, P., & Lee, S. (2019). Vehicle Routing Problem with Drones for Last Mile Delivery. *Procedia Manufacturing, 39*, 314-324.

Sacramento, D., Pisinger, D., & Ropke, S. (2019). An adaptive large neighborhood search metaheuristic for the vehicle routing problem with drones. *Transportation Research Part C-Emerging Technologies, 102*, 289-315.

Luo, Q., Wu, G., Ji, B., Wang, L., & Suganthan, P. N. (2022). Hybrid Multi-Objective Optimization Approach with Pareto Local Search for Collaborative Truck-Drone Routing Problems Considering Flexible Time Windows. *IEEE Transactions on Intelligent Transportation Systems, 23*(8), 13011-13025.

Kim, G. (2018). Optimal Vehicle Routing for Parcel Delivery with Considering Two Time Periods. *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEE IEEM)*, 2019-December, 918-922.

Han, Y. Q., Li, J. Q., Liu, Z., Liu, C., & Tian, J. (2020). Metaheuristic algorithm for solving the multi-objective vehicle routing problem with time window and drones. *International Journal of Advanced Robotic Systems, 17*(2).

Ulmer, M. W., & Thomas, B. W. (2018). Same-day delivery with heterogeneous fleets of drones and vehicles. *Networks, 72*(4), 475-505.

Budak, G., & Chen, X. (2023). A Hybrid Mathematical Model for Flying Sidekick Travelling Salesman Problem with Time Windows. *Operations Research Forum, 4*(4), 1-21.

Ren, X. X., Fan, H. M., Bao, M. X., & Fan, H. (2023). The time-dependent electric vehicle routing problem with drone and synchronized mobile battery swapping. *Advanced Engineering Informatics, 57*(1).

Peng, Y., Ren, Z., Yu, D. Z., & Zhang, Y. (2025). Transportation and carbon emissions costs minimization for time-dependent vehicle routing problem with drones. *Computers & Operations Research, 176*.

Masone, A., Poikonen, S., & Golden, B. L. (2022). The multivisit drone routing problem with edge launches: An iterative approach with discrete and continuous improvements. *Networks, 80*(2), 193-215.

Murray, C. C., & Raj, R. (2020). The multiple flying sidekicks traveling salesman problem: Parcel delivery with multiple drones. *Transportation Research Part C-Emerging Technologies, 110*, 368-398.

Stodola, P., & Kutej, L. (2024). Multi-Depot Vehicle Routing Problem with Drones: Mathematical formulation, solution algorithm and experiments. *Expert Systems with Applications, 241*.

Salama, M. R., & Srinivas, S. (2022). Collaborative truck multi-drone routing and scheduling problem: Package delivery with flexible launch and recovery sites. *Transportation Research Part E-Logistics and Transportation Review, 164*.

Yin, Y., Yang, Y., Yu, Y., Wang, D., & Cheng, T. C. E. (2023). Robust vehicle routing with drones under uncertain demands and truck travel times in humanitarian logistics. *Transportation Research Part B-Methodological, 174*(1).

Thomas, T., Srinivas, S., & Rajendran, C. (2024). Collaborative truck multi-drone delivery system considering drone scheduling and en route operations. *Annals of Operations Research, 339*(1-2), 693-739.

Meng, Z., Yu, K., & Qiu, R. (2024). Location-routing optimization of UAV collaborative blood delivery vehicle distribution on complex roads. *Complex & Intelligent Systems, 10*(6), 8127.

Cai, B., Lu, F., & Zhou, L. (2023). Energy-Aware Routing Algorithm for Mobile Ground-to-Air Charging. *arXiv*.

Gao, J., Zhen, L., & Wang, S. (2023). Multi-trucks-and-drones cooperative pickup and delivery problem. *Transportation Research Part C-Emerging Technologies, 157.*

Faiz, T. I., Vogiatzis, C., Liu, J., & Noor-E-Alam, M. (2024). A robust optimization framework for two-echelon vehicle and UAV routing for post-disaster humanitarian logistics operations. *Networks, 84*(2), 200-219.

Tamke, F., & Buscher, U. (2021). A branch-and-cut algorithm for the vehicle routing problem with drones. *Transportation Research Part B-Methodological, 144*, 174-203.

Cavani, S., Iori, M., & Roberti, R. (2021). Exact methods for the traveling salesman problem with multiple drones. *Transportation Research Part C-Emerging Technologies, 130*, Article 103280.

Boccia, M., Mancuso, A., Masone, A., & Sterle, C. (2024). Exact and heuristic approaches for the Truck-Drone Team Logistics Problem. *Transportation Research Part C-Emerging Technologies, 165*.

Yin, Y., Li, D., Wang, D., Ignatius, J., Cheng, T. C. E., & Wang, S. (2023). A branch-and-price-and-cut algorithm for the truck-based drone delivery routing problem with time windows. *European Journal of Operational Research, 309*(3), 1125-1144.

Kuo, R. J., Lu, S. H., Lai, P. Y., & Mara, S. T. W. (2022). Vehicle routing problem with drones considering time windows. *Expert Systems with Applications, 191*, Article 116264.

Mulumba, T., & Diabat, A. (2024). Optimization of the drone-assisted pickup and delivery problem. *Transportation Research Part E-Logistics and Transportation Review, 181*.

Shi, G., & Tokekar, P. (2023). Decision-Oriented Learning with Differentiable Submodular Maximization for Vehicle Routing Problem. *arXiv*.

Faiz, T. I., Vogiatzis, C., & Noor-E-Alam, M. (2020). Computational Approaches for Solving Two-Echelon Vehicle and UAV Routing Problems for Post-Disaster Humanitarian Operations. *arXiv*.

Ghaffar, M. A., Peng, L., Aslam, M. U., Adeel, M., & Dassari, S. (2024). Vehicle-UAV Integrated Routing Optimization Problem for Emergency Delivery of Medical Supplies. *Electronics, 13(*18), Article 3650.

Deng, X., Guan, M., Ma, Y., Yang, X., & Xiang, T. (2022). Vehicle-Assisted UAV Delivery Scheme Considering Energy Consumption for Instant Delivery. *Sensors, 22*(5), Article 2045.

Li, Y., Yang, W., & Huang, B. (2020). Impact of UAV Delivery on Sustainability and Costs under Traffic Restrictions. *Mathematical Problems in Engineering, 2020*(1).

Stodola, P., & Kutej, L. (2023). Multi-Depot Vehicle Routing Problem with Drones: Mathematical Formulation, Solution Algorithm and Experiments.*SSRN*.

Ming Han,Ya-Bin Wang,Xiang Chen & Xing Zhao. (2019). (A Research on Vehicle and UAV Routing Problem during Distribution Based on IAMMAS). *IOP Conference Series: Materials Science and Engineering,688*(4)

Konstantinos Kouretas & Konstantinos Kepaptsoglou. (2025). (Stochastic Planning of Synergetic Conventional Vehicle and UAV Delivery Operations). Drones,9(5),359-359

Sadok, A., Euchi, J., & Siarry, P. (2024). Vehicle routing with multiple UAVs for the last-mile logistics distribution problem: hybrid distributed optimization. *Annals of Operations Research*, 1-41.