

REVIEW

Open Access



Advances in truck–drone cooperative delivery routing and coordination: a review

Yang Liu¹, Yi Fei² and Changxi Ma^{1*}

Abstract

Unmanned Aerial Vehicle (UAV)–vehicle cooperative delivery has emerged as a promising paradigm for addressing the growing complexity of urban and regional logistics. By combining the capacity and network coverage of ground vehicles with the flexibility and accessibility of UAVs, such systems offer new opportunities to improve delivery efficiency, responsiveness, and sustainability across diverse operational contexts. In recent years, research in this field has expanded rapidly, producing a wide range of models, algorithms, and application-driven studies. This paper provides a comprehensive review of UAV–vehicle cooperative delivery research, synthesizing advances in system configurations, coordination mechanisms, modeling approaches, and solution methodologies, including optimization-based, heuristic, hybrid, and learning-driven frameworks. Empirical evidence from major application domains, such as urban parcel logistics, emergency and humanitarian operations, infrastructure inspection, and on-demand services, is examined to reveal how system design and operational conditions jointly shape performance. Beyond summarizing existing work, this review identifies fundamental modeling, operational, and sustainability challenges that continue to hinder large-scale deployment, including synchronization fragility, energy and uncertainty management, regulatory constraints, and scalability. By consolidating fragmented research strands into a unified analytical perspective, this review aims to support the transition of UAV–vehicle cooperative delivery from isolated pilot studies toward robust, scalable, and policy-relevant transportation systems.

Keywords UAV–vehicle cooperative delivery, Truck–drone hybrid routing, Vehicle routing problem (VRP), Traveling salesman problem with drones (TSP-D), Sustainable logistics systems

1 Introduction

E-commerce growth and on-demand consumption have intensified urban delivery pressures in dense cities, where congestion, curbside scarcity, and environmental constraints undermine the reliability of conventional truck-only distribution [1, 2]. Unmanned aerial vehicles (UAVs) have therefore been explored as a complementary mode

because they can bypass ground bottlenecks and provide direct access over short distances [3, 4]. Yet UAV-only delivery remains constrained by payload, battery endurance, operational sensitivity to weather, and airspace regulation. This has encouraged hybrid ground-aerial systems in which vehicles provide capacity and network reach, and UAVs enhance local service accessibility, giving rise to growing interest in UAV-vehicle cooperative delivery [5, 6].

Research on UAV-vehicle cooperative delivery has expanded steadily over recent years, giving rise to a broad and heterogeneous body of literature. Early studies primarily focused on parcel distribution problems [7, 8], while subsequent work has extended the scope to urban

*Correspondence:

Changxi Ma
machangxi@mail.lzjtu.cn

¹School of Traffic and Transportation, Lanzhou Jiaotong University,
Lanzhou 730070, China

²School of Software, Henan University of Engineering,
Zhengzhou 451191, China

Table 1 Comparison of representative prior reviews and this review

Reference	Problem domain covered	What is reviewed	Coverage of coordination mechanisms	Gap addressed by this review
Chung et al. (2020) [26]	Broad drone operations and drone-truck combined operations	• Optimization models for drone operations • Mathematical formulations for drone-truck combined operations • Exact methods • Heuristic and metaheuristic methods • Operational implementation issues	Coordination is discussed mainly through synchronization requirements, operational coupling, and implementation constraints, but not organized as a dedicated coordination taxonomy.	Truck–drone cooperative delivery is embedded within a broader review of drone operations rather than synthesized through an integrated routing-and-coordination framework.
Macrina et al. (2020) [41]	Drone-aided routing in parcel delivery	• Drone-aided TSP/VRP-type formulations • Routing decision structures for parcel delivery • Operations research models • Exact algorithms • Heuristic/metaheuristic algorithms	Coordination is discussed mainly within routing formulations, especially through drone launch, service, and recovery decisions.	Provides a strong OR-oriented review, but gives less explicit attention to broader coordination structures, infrastructure settings, and cross-application integration.
Viloria et al. (2021) [42]	UAV-related problems in the broader VRP family	• UAV-related VRP formulations • Objective functions and constraints • Hybrid truck–drone variants • Solution methods for UAV-enabled routing	Coordination is mentioned as one element within UAV-enabled routing variants, rather than reviewed as a central topic.	Reviews UAV-related routing variants broadly, but does not focus specifically on truck–drone cooperative delivery as an integrated system.
Li et al. (2021) [43]	GV-UAV routing under two-echelon structures	• Two-echelon routing formulations • Echelon-connection structures • Satellite synchronization problems • Related exact and heuristic methods	Coordination is reviewed mainly through echelon connection, satellite synchronization, and layer-to-layer interaction.	Strong on two-echelon synchronization mechanisms, but narrower than a full review of cooperative delivery configurations, methods, and applications.
Stodola et al. (2024) [44]	Drone-based models in logistics	• Logistics-oriented drone models • Classification of drone-based logistics problems • Optimization approaches in logistics settings • Research avenues across logistics applications	Coordination is discussed at a general logistics level, but not unpacked in depth as a dedicated truck–drone mechanism review.	Offers a broad logistics classification, but ground–air coordination is not synthesized in the same depth as in dedicated truck–drone delivery reviews.
Dukkanci et al. (2024) [45]	Facility location and network design for drone delivery	• Facility-location models • Network design formulations • Infrastructure planning problems • Optimization methods for facility design	Coordination is discussed mainly through facility support, infrastructure design, and vehicle–facility interaction.	Focuses on location and infrastructure decisions rather than routing-and-coordination mechanisms central to truck–drone delivery operations.
Boysen et al. (2024) [46]	Routing problems for cooperated trucks and drones	• Routing problem variants for cooperated truck–drone systems • Constraints and objectives • Launch/recovery patterns • Exact methods • Heuristics and metaheuristics	Coordination is explicitly reviewed through cooperative modes, routing variants, launch/recovery patterns, and related interaction structures.	Closely related to our topic, but is more centered on routing problem variants and classifications than on a unified synthesis of structural, operational, and methodological dimensions.
Grippa et al. (2024) [47]	Truck-drone routing problem approaches	• Exact approaches for TDRP • Heuristic approaches • Metaheuristic approaches • Comparative discussion of algorithmic trends	Coordination is discussed mainly through routing assumptions and algorithmic treatment rather than as a standalone analytical dimension.	Strong on solution approaches, but narrower than a broader synthesis of coordination mechanisms and application contexts.
Luo et al. (2025) [48]	Mathematical models for TDRP	• OTOD formulations • OTMD formulations • MTMD formulations • Parameter structures and assumptions • Related solution methods	Coordination is reflected through modeling assumptions and operational configurations, but not reviewed as an independent comparative dimension.	Provides a strong formal model taxonomy, but is not intended as a wider system-level review of coordination mechanisms and broader application contexts.
Arishi and Ahuja (2025) [30]	MARL-based truck–drone routing in smart logistics	• MARL methods for truck–drone routing • Centralized/decentralized learning schemes • Policy coordination mechanisms • Learning-based decision frameworks	Coordination is explicitly discussed in the context of decentralized/centralized learning, policy interaction, and real-time decision making.	Method-specific review that does not aim to synthesize the broader truck–drone cooperative delivery literature.

Table 1 (continued)

Reference	Problem domain covered	What is reviewed	Coverage of coordination mechanisms	Gap addressed by this review
Freitas et al. (2025) [49]	Collaborative truck–drone delivery in last-mile logistics	• CTD-LMD system configurations • Operational assumptions • Collaborative delivery structures • Solution approaches in last-mile settings	Coordination is explicitly discussed through collaborative delivery structures, launch/recovery arrangements, and operational categories.	Very close in scope, but remains centered on CTD-LMD categorization and last-mile contexts, with less explicit integration of structural and operational dimensions across broader cooperative-delivery settings.
This review	Truck–drone cooperative delivery routing and coordination across configurations, mechanisms, methods, and applications	• Structural taxonomy of cooperative delivery systems • System configurations and operational settings • Coordination and interaction modes • Modeling assumptions and problem attributes • Optimization, heuristic, hybrid, and learning-based methods • Comparative discussion across application contexts	Coordination is reviewed explicitly and systematically through system configurations, interaction modes, synchronization logic, and operational formulations.	Integrates structural taxonomy, coordination mechanisms, modeling and solution strategies, and cross-context comparative analysis within a single framework, thereby addressing the fragmentation of prior reviews.

food delivery [9–11], medical and emergency supply distribution [12, 13], and hybrid passenger–parcel service systems [14, 15]. As application contexts diversified, research attention gradually shifted toward coordination issues between ground vehicles and UAVs, including launch and recovery [16, 17], task assignment [18, 19], routing synchronization [20, 21], and energy-aware scheduling [22–24]. Correspondingly, a wide range of methodological approaches has been adopted, ranging from analytical optimization [25–27] and mixed-integer programming models [5] to heuristic and metaheuristic algorithms [12, 28, 29], simulation-based frameworks [7], and data-driven or learning-based methods [30, 31]. Overall, existing studies present a wide range of problem formulations and solution approaches that are shaped by different operational assumptions and research objectives.

This growing methodological diversity also reflects a gradual shift from idealized problem settings toward operationally grounded coordination problems. In parallel, emerging real-world services are starting to provide concrete evidence on what coordination mechanisms and modeling assumptions can scale in practice. As of late 2025, publicly reported deployments indicate that truck-supported drone delivery is moving beyond pilot demonstrations and entering early routine operations in selected service areas. Amazon Prime Air reports an optional \$4.99 fee for eligible drone orders [32, 33], while Meituan reports nationwide certification for low altitude logistics and an operational scale on the order of dozens of routes and hundreds of thousands of completed orders [34, 35].

Although a substantial body of review studies has examined UAV-vehicle cooperative delivery, existing reviews have mostly approached the topic from separate perspectives rather than providing an integrated

understanding of truck–drone cooperative delivery as a whole. General surveys on delivery routing and UAV-supported logistics established early conceptual foundations, but typically treated cooperative truck-UAV operations as one variant within broader routing problems rather than as a dedicated research domain [36–38]. Reviews focusing on drone logistics and facility-based operations further discussed system architectures and infrastructure considerations, yet often addressed ground and aerial interactions only at an aggregate level without detailed treatment of coordination mechanisms [3, 39, 40]. More specialized surveys on collaborative truck-drone routing and two-echelon ground-aerial systems provided deeper insights into specific problem families, while method-oriented reviews emphasized algorithmic developments such as multi-agent reinforcement learning [24, 31]. As a result, the literature still lacks a unified synthesis that connects system configurations, coordination mechanisms, modeling assumptions, solution methods, and application settings.

To clarify the positioning of this review, Table 1 compares representative prior studies in terms of the problem domains covered, the modeling and solution methods reviewed, the treatment of coordination mechanisms, and the main gap addressed here. The comparison indicates that existing reviews have mainly concentrated on specific problem settings, methodological streams, or application contexts, with relatively limited effort to jointly connect structural configurations, operational coordination, modeling assumptions, and solution methods within a unified framework.

Building on this positioning, this review makes three contributions. First, it develops an integrated analytical framework linking system configurations, coordination mechanisms, modeling assumptions, and solution methods. Second, it compares evidence across application

domains to distinguish relatively transferable findings from assumption-dependent results. Third, it identifies reproducibility and comparability as methodological issues and proposes reporting dimensions to support cumulative research in truck–drone cooperative delivery.

2 Systematic review methodology

This review follows a transparent and reproducible procedure to identify, screen, and synthesize studies on truck–drone hybrid routing and coordination. Records were retrieved from Scopus, Web of Science Core Collection, and IEEE Xplore, supplemented by targeted searches in ScienceDirect and backward and forward citation tracking [50]. The search covered publications from 2015 to 2026 and was conducted in the title, abstract, and keyword fields. Search strings combined four term groups: ground vehicle terms (e.g., truck, vehicle, van, and mobile depot), drone terms (e.g., drone, UAV, and unmanned aerial vehicle), decision terms (e.g., routing, VRP, TSP, scheduling, dispatch, and coordination*), and logistics context terms (e.g., delivery, logistics, and distribution).

Eligible studies were limited to peer-reviewed journal articles and full conference papers that modeled explicit truck–drone interaction and included a formal routing, scheduling, or dispatch formulation, together with a specified solution approach and some form of computational, simulation-based, or empirical evaluation. Studies without formal decision models, studies focused solely on drone hardware, communication, or perception without routing-related decisions, and non-peer-reviewed short items were excluded.

Screening was conducted in two stages. Title-and-abstract screening removed records that were clearly

outside truck–drone cooperative delivery or did not involve routing, scheduling, dispatching, or coordination decisions. Full-text assessment further required explicit ground–air interaction, a formal decision formulation, a specified solution method, and computational, simulation-based, or empirical evaluation. Potential coverage bias may remain because the review is limited by database selection, English-language and peer-reviewed publication coverage, inaccessible full texts, and terminology differences across research communities. Backward and forward citation tracking was used to mitigate these limitations.

A total of 372 records were identified through database searches, with 18 additional records obtained through backward and forward citation tracking. After deduplication, screening, and full-text assessment against the pre-defined eligibility criteria, 136 studies were retained for the final review. The detailed study selection process is presented in Fig. 1.

For each included study, information was extracted on system configuration, operational setting, dynamics and uncertainty, objectives and performance metrics, and solution approach. Specifically, we coded features such as fleet size, launch-and-retrieve mode, synchronization assumptions, battery or charging rules, time windows, service times, no-fly zones, stochastic demand, weather impacts, rolling-horizon or online mechanisms, and methodological categories including exact, heuristic/metaheuristic, decomposition/hybrid, and learning-based approaches.

To further characterize the development of the field, we also conducted a keyword co-occurrence analysis in VOSviewer using the bibliographic records retained after

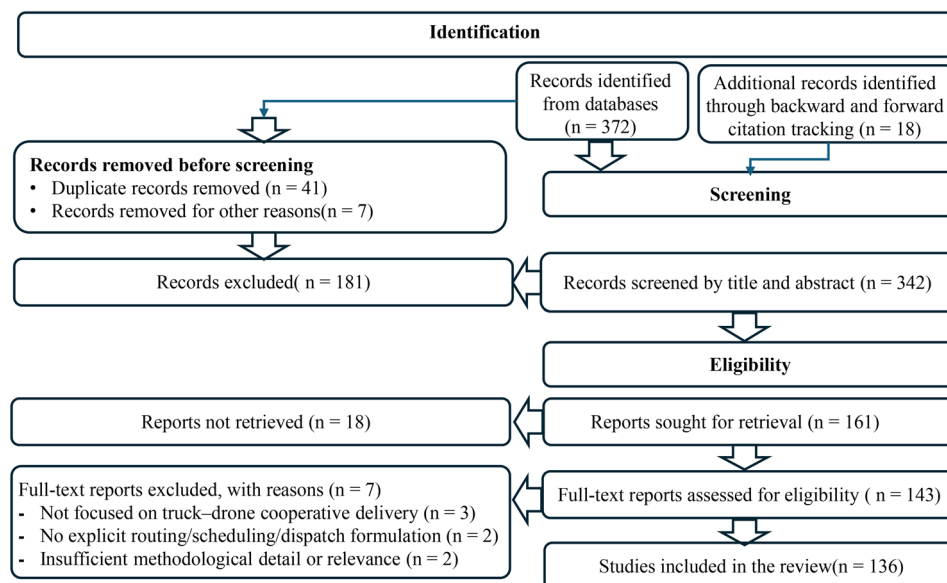


Fig. 1 PRISMA-style flow diagram

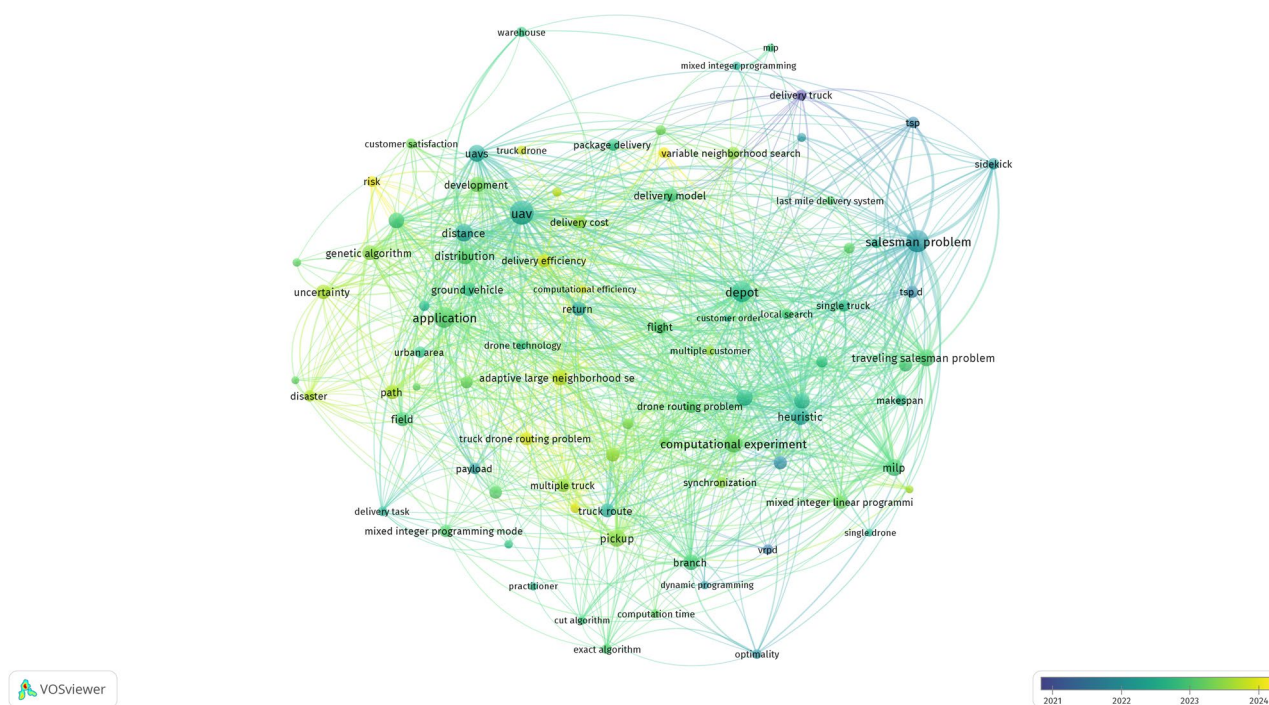


Fig. 2 Keyword co-occurrence network of UAV–vehicle cooperative delivery research (2015–2026)

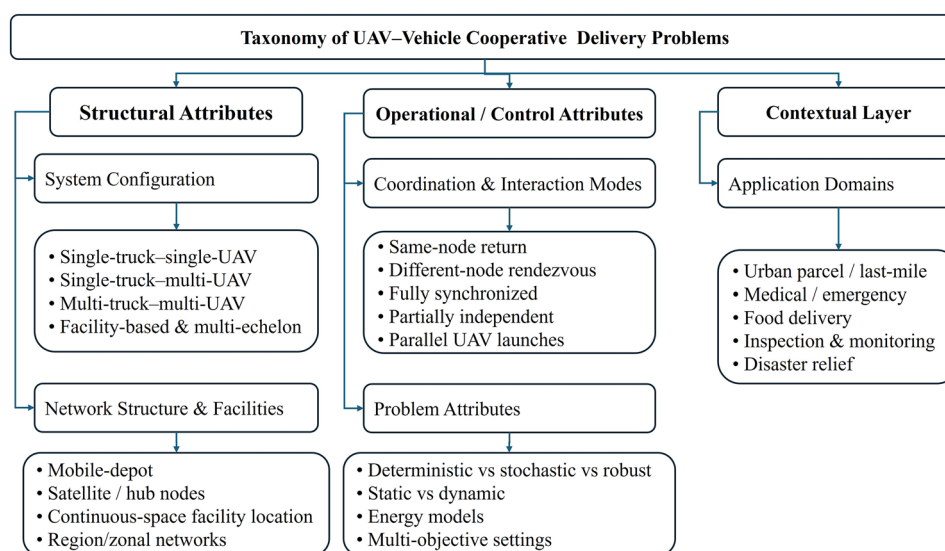


Fig. 3 Multidimensional taxonomy for UAV–vehicle cooperative delivery problems

screening, as shown in Fig. 2. The temporal distribution indicates a gradual shift from optimisation-centred research toward more operationally oriented themes, including uncertainty, on-demand services, and multi-drone coordination.

The diversity of UAV–vehicle cooperative delivery systems has produced a broad landscape of problem formulations, shaped by differences in system architecture, operational interactions, modeling assumptions, and spatial contexts. To provide a coherent structure for

interpreting these heterogeneous studies, Fig. 3 presents a multidimensional taxonomy. The framework distinguishes structural attributes—including system configuration, network structure, and supporting facilities—from operational and control attributes, such as coordination and interaction modes and problem-specific modeling features. Application domains are treated as a contextual layer that influences design choices, assumptions, and performance metrics, but does not constitute an independent modeling dimension.

2.1 Taxonomy of UAV–vehicle cooperative delivery problems

Although these dimensions are separated for analytical clarity, they are not independent in practice. Structural attributes define the physical and infrastructural setting within which cooperative delivery is organized, while operational and control attributes describe how synchronization, interaction, and decision-making are realized within that setting. For example, differences in fleet composition, launch-and-retrieval arrangements, or facility availability may determine whether same-node return, moving rendezvous, parallel UAV sorties, or cross-layer coordination are feasible. Conversely, operational requirements such as synchronization intensity, uncertainty handling, and service constraints may motivate different structural designs. These relationships also help explain why studies with similar delivery settings may adopt different model structures. Facility-supported systems often require location–routing formulations, whereas moving rendezvous, parallel UAV launches, dynamic demand, or uncertain accessibility may lead to stronger synchronization constraints, battery-feasibility checks, stochastic or robust formulations, rolling-horizon models, or learning-based approaches. This taxonomy therefore provides not only a basis for organizing problem variants, but also a way to interpret the modeling choices observed across the literature.

2.1.1 System configuration

A central dimension of the taxonomy is **system configuration**, which characterizes how vehicles and UAVs are organized as cooperative delivery units and how their operational roles are coupled. Figure 4 illustrates three representative configuration paradigms based on the number of participating vehicles and UAVs.

Early studies predominantly examined single-truck single-UAV configurations, as shown in Fig. 4(a) [51–54]. These formulations capture the fundamental operational logic of UAV launch, remote service, and retrieval. They typically impose strict temporal consistency between the truck and the UAV, highlighting synchronization feasibility as a key concern [36, 55, 56]. As research progressed, single-truck multi-UAV configurations emerged, as illustrated in Fig. 4(b), allowing multiple UAVs to operate from the same vehicle. This configuration enhances service capacity through parallel sorties but introduces additional coordination challenges, including inter-UAV dependencies, battery sequencing, and more complex rendezvous feasibility conditions [37]. At a larger scale, multi-truck multi-UAV configurations, shown in Fig. 4(c), extend cooperative delivery to network-level operations, such as humanitarian logistics, emergency response, and large-scale urban services, where multiple vehicles function as distributed mobile coordination units [45, 57]. Overall, system configuration defines the basic cooperative structure through which vehicles and UAVs jointly execute delivery tasks.

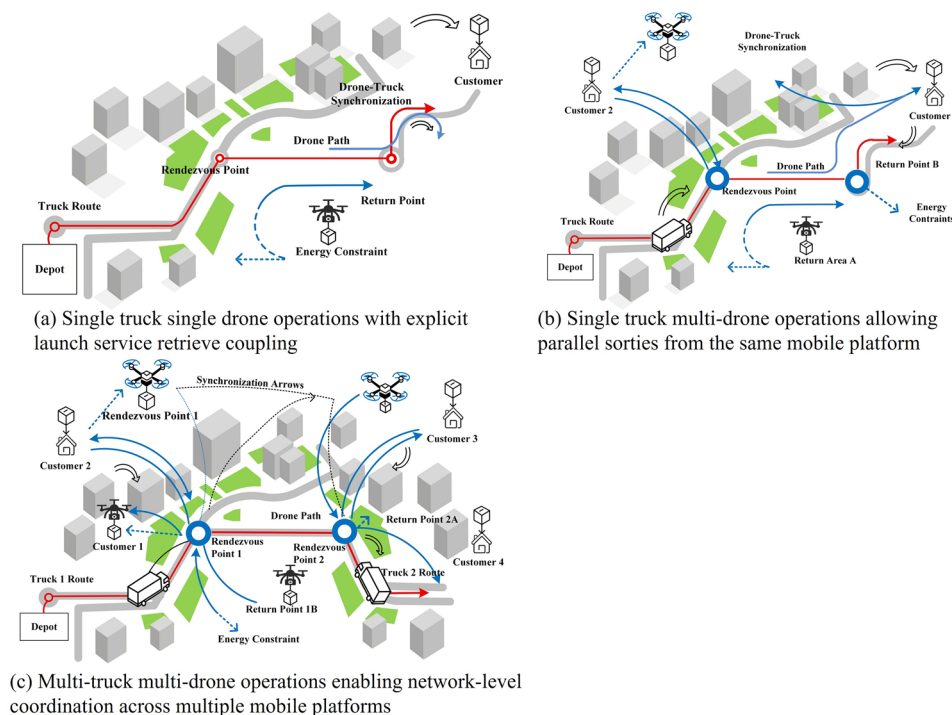


Fig. 4 Schematic illustrations of three representative ground–air cooperation paradigms

2.1.2 Network structure and facilities

The dimension of network structure and facilities describes the spatial and infrastructural context in which UAV-vehicle cooperative systems operate. In single echelon mobile networks, UAV operations are fully supported by trucks acting as mobile depots, a setting commonly adopted in early Flying Sidekick Traveling Salesman Problem (FSTSP) and the Traveling Salesman Problem with Drone (TSPD) studies [37, 51]. Facility-supported networks extend this structure by introducing fixed infrastructure elements such as drone stations, micro-hubs, or intermediate depots, which can expand UAV service coverage or provide recharging and staging capabilities [43, 45]. More advanced studies consider continuous space facility location models, in which the placement of drone stations is optimized to improve aerial accessibility across heterogeneous demand distributions. Multimodal or transit-integrated frameworks further embed UAV operations within broader transportation systems, such as rail or bus corridors, enabling coordinated interactions between ground and aerial modes [58]. In emergency logistics and disaster response scenarios, region-based or zonal network structures are often employed to partition service areas and coordinate multi-agent operations across subregions [59, 60]. Network structure and facilities shape the operational environment and link routing decisions with infrastructure availability and environmental constraints.

2.1.3 Coordination and interaction modes

Closely connected to physical configuration are coordination and interaction modes, which describe how vehicles and UAVs synchronize their movement across time and space. One basic distinction is whether the UAV must return to the same launch node (same-node return) or may rendezvous at a different location. Same-node return models dominate early TSP-D formulations [51], reducing coordination requirements by constraining UAV paths. In contrast, different node rendezvous allows the truck to continue moving during UAV sorties, reducing idling but introducing more demanding temporal and energy consistency constraints [61]. A second dimension concerns whether operations are fully synchronized requiring the truck to wait during UAV sorties, or partially independent, where both platforms move simultaneously, and meeting feasibility becomes a moving target [17]. In multi-UAV settings, UAVs may be launched sequentially or in parallel depending on platform capacity and safety restrictions [37]. Two-echelon systems introduce additional cross-layer interactions between trucks, satellite depots, and UAVs [43, 57], requiring coordination across mobile and fixed infrastructure. Coordination modes, therefore determine both

the temporal flexibility and the coupling intensity of system operations, directly affecting model complexity.

2.1.4 Problem attributes and modeling assumptions

Problem attributes and modeling assumptions characterize the analytical structure of different formulations. Deterministic models, often used in early TSPD and FSTSP studies, assume fixed travel times and predictable energy consumption [62], providing a stable foundation for analyzing synchronization and route feasibility. As researchers sought to capture real-world variability, stochastic and robust formulations were introduced, accounting for uncertain wind conditions, stochastic service times, variable energy consumption, or demand arrival randomness [63]. Temporal structure further distinguishes static models, in which all requests are known in advance and are often addressed using exact or decomposition-based methods, from dynamic models that accommodate real-time arrivals, customer updates, or adaptive routing decisions, as seen in on-demand truck-UAV collaboration [64] and food delivery applications [65]. Additional heterogeneity arises from differing assumptions on UAV service times, load-dependent energy models [66], or multi-objective formulations that balance efficiency, energy, resilience, or environmental criteria [67]. Together, these attributes determine the mathematical structure of the problem and the types of algorithms that are computationally feasible.

2.1.5 Application domains

Finally, application domains and task characteristics introduce contextual factors that influence model assumptions, operational constraints, and performance objectives [62, 68]. On-demand food delivery and high-frequency commercial logistics introduce narrow service windows, time-varying arrivals, and customer-centric objectives [11, 69]. Medical logistics and emergency response emphasize strict time sensitivity, safety requirements, and reliability, leading to formulations with tighter service time and energy constraints [8, 17, 70]. Disaster response settings emphasize UAV accessibility in disrupted networks, often combining multi-agent coordination with regional partitioning [71, 72]. Multimodal delivery logistics integrate UAVs with public transit or freight movements [73–75], requiring cross-modal synchronisation [76–78]. While these applications are not independent modeling dimensions, they shape the assumptions and objective structures of many problem variants.

3 Methodologies for UAV-Vehicle cooperative delivery

The increasing complexity of UAV-vehicle cooperative delivery problems has led to a wide range of solution methodologies. When synchronization, energy constraints, facility decisions, and multi-vehicle interactions are considered, even moderately sized instances become computationally challenging, motivating approaches that span exact optimization, heuristics and metaheuristics, decomposition and hybrid frameworks, and learning-based methods. These approaches differ in their optimization paradigms and in how they exploit problem structure, manage uncertainty, and trade off solution quality against computational efficiency.

Section 2.1.1 synthesizes these methodologies in a structured manner. It first introduces the core mathematical formulations underlying UAV-vehicle cooperative delivery problems, followed by a review of exact methods, heuristics and metaheuristics, and decomposition and hybrid approaches. The section then discusses learning-based and multi-agent methods and highlights emerging directions related to scalability and complexity management. Figure 5 summarizes this methodological taxonomy and illustrates the progression from exact methods to more flexible and adaptive solution strategies.

3.1 Mathematical formulations and modeling frameworks

This subsection introduces the core modeling paradigms used to mathematically represent UAV-vehicle cooperative delivery problems. Most studies rely on mixed integer linear programming (MILP) formulations that extend classical vehicle routing or traveling salesman models by explicitly incorporating UAV operations. Early formulations, such as the flying sidekick TSP proposed by Agatz et al. [62], introduced coupled decision variables for truck routing, UAV sorties, and synchronization constraints to capture launch-serve-rendezvous processes. Subsequent refinements emphasized tighter representations of endurance limits and temporal consistency, particularly in single-UAV settings [52, 54]. These models established a common structural backbone for early UAV-vehicle cooperation studies.

As system complexity increases, modeling frameworks expand to accommodate multiple UAVs and parallel operations. Multi-UAV formulations introduce additional constraints for UAV sequencing, launch conflicts, and non-overlapping sorties, significantly enlarging the decision space. Representative studies incorporate fleet-indexed variables and timing constraints to manage parallel UAV activities and vehicle-UAV interactions [17, 79]. In high-frequency or heterogeneous delivery contexts, assignment variables are often required to coordinate multiple UAVs with distinct capabilities [28]. More recent work also adopts learning-based formulations to

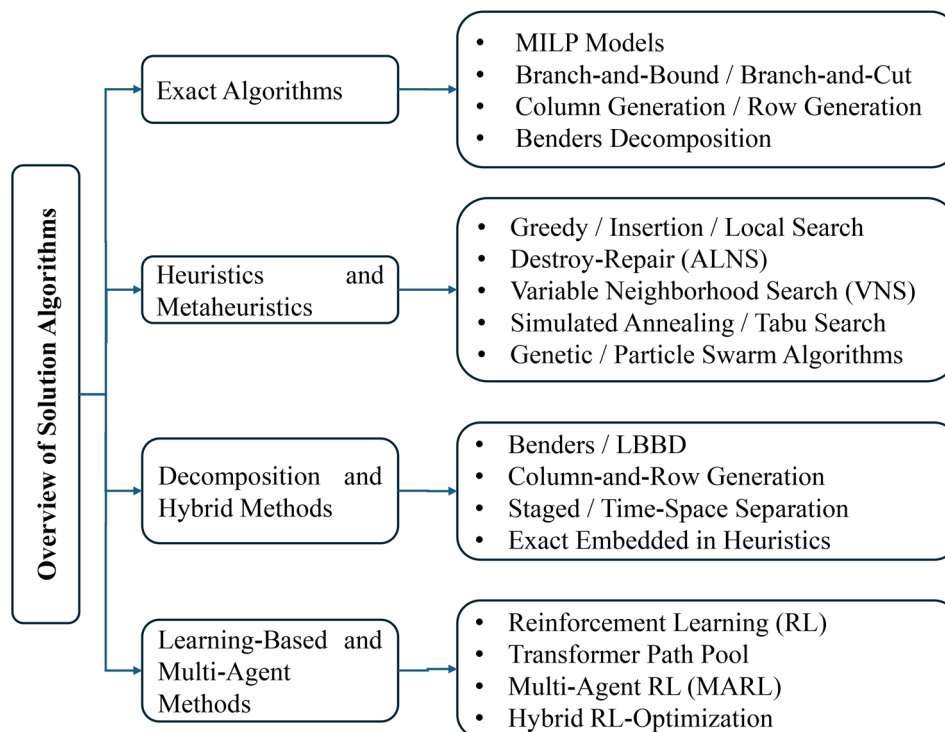


Fig. 5 Taxonomy of solution methodologies for UAV-vehicle cooperative delivery

address temporal coupling and uncertainty in dynamic environments [80].

Facility-supported and multi-echelon systems further enrich the modeling structure. In these settings, UAV operations are no longer fully anchored to a single truck, and additional decision layers are introduced for facility assignment, recharging, and staging. Two echelon formulations integrate depot selection and battery replenishment into routing decisions [41, 81], while continuous space models optimize facility locations jointly with UAV endurance constraints [78]. By decoupling UAV operations from individual vehicles, such frameworks enhance system scalability and operational flexibility in delivery [67].

Energy consumption and uncertainty form another critical modeling dimension. Early studies typically adopted simplified linear battery models [54, 62], whereas more recent formulations incorporate stochastic or robust representations of energy use, travel times, and environmental conditions. Scenario-based and robust models adjust sortie feasibility under demand and weather uncertainty, reshaping synchronization and routing decisions accordingly [82, 83].

Dynamic and on-demand settings motivate time-expanded modeling structures. Time-expanded, or synchronization-graph formulations represent feasible rendezvous options across temporal layers, enabling flexible responses to real-time requests and evolving vehicle states. Such structures are particularly suited to dynamic dispatching and learning-driven decision processes in UAV-vehicle cooperation [84, 85].

3.2 Exact algorithms

Exact algorithms aim to deliver provably optimal solutions (or rigorous optimality bounds) for UAV-vehicle cooperative delivery problems under synchronization, routing, and energy constraints. Compared with classical VRP/TSP settings, their computational difficulty mainly arises from the tight coupling between truck routing decisions and drone sortie timing/feasibility, which typically yields large-scale mixed integer models and computationally demanding pricing or separation subproblems.

A dominant exact paradigm relies on branch and price and column generation frameworks. Its tractability largely depends on how launch and retrieval synchronization is modeled, so that the pricing problem remains efficiently solvable. Schmidt et al. (2024) [86] proposed a branch price and cut algorithm for the VRP-D, utilizing forward and bidirectional labeling over artificial networks to solve instances up to 50 vertices, highlighting the role of carefully designed labeling and dominance rules in synchronization aware pricing. Roberti & Ruthmair (2021) [54] studied an exact approach for a TSP-D variant and showed that integrating truck-drone coupling

within a decomposition/route generation framework can certify optimality on small to moderate instances.

Beyond deterministic settings, exact methods have been extended to robust/stochastic variants and richer operational features (e.g., multi-trip operations and heterogeneous fleets), typically by introducing additional decomposition layers. Yin et al. (2023) [83] devised a branch and price and cut algorithm for robust VRP-D under uncertain demands and travel times, with bidirectional labeling accelerating pricing subproblems. In parallel, robust formulations with service deadlines often adopt Benders-type decomposition to separate strategic routing decisions from uncertainty-dependent feasibility/recourse, as exemplified by Deng et al. (2024) [87] in minimizing delay risks under uncertainty.

For facility-integrated and two-echelon variants, the hierarchical structure of decisions motivates decomposition based exact algorithms, since truck level routing/location choices and drone-level feasibility/synchronization constraints can be modularized and strengthened through targeted cuts and subproblem designs [88].

Exact algorithms are most valuable when provable bounds are required, and instance sizes remain moderate, serving as a benchmarking reference for evaluating heuristic and learning-based methods. Their practical bottleneck is scalability: time-expanded synchronisation, multi-trip/multi-drone settings, and facility/2-echelon coupling can rapidly increase model size and pricing complexity, making tailored labeling, dominance rules, and decomposition designs essential. Moreover, cross-study performance comparisons should be interpreted with caution because energy models, rendezvous policies, and discretization schemes differ across papers and directly affect computational hardness. These considerations motivate the hybrid and decomposition-assisted paradigms summarized in Table 2.

3.3 Heuristics and metaheuristics algorithms

Heuristic and metaheuristic algorithms constitute the mainstream solution paradigm for truck-drone cooperative routing when exact methods become computationally prohibitive. Their core idea is to trade optimality guarantees for scalability by exploring structured neighborhoods around incumbent solutions while explicitly enforcing feasibility with respect to synchronization and drone endurance. In this literature, feasibility is not a peripheral constraint checking step; rather, it is tightly intertwined with how a route is encoded (e.g., truck sequence plus drone sorties) and how neighborhood moves are defined.

Early and baseline heuristics typically construct feasible solutions through greedy insertion and cost-saving rules, providing fast initial routes and enabling large-scale scenario exploration. Figliozzi (2020) [95], for instance,

Table 2 Summary of exact algorithms

Reference	Algorithm Type	Problem Type	Model Type	# Trucks	# Drones	Synchronization (Y/N)	Objective	Notes
Cavani et al. (2021) [55]	B&C	TSP-MD	MILP	1	M	Y	Minimize makespan	Multi-drone; energy model; multi-trip drones allowed.
Stokkink et al. (2025) [76]	B&P	LRP	MIP	M	M	Y	Minimize cost	Location routing; time indexed; charging stations.
Boccia et al. (2024) [29]	B&C	TDTL	MILP	1	1	Y	Minimize makespan	Multi-trip; energy consumption; different land/hover at rendezvous.
Montemanni et al. (2024) [89]	B&P	PDSTSP	CP/MILP	1	M	N	Minimize makespan	Parallel scheduling; collective drones; energy model.
Liu et al. (2025) [84]	B&P	Drone Scheduling	MILP	1	M	Y	Minimize cost	Battery replacement; time indexed; multi-trip.
Delle Donne et al. (2025) [90]	CG	Multi-modal Routing	MIP	M	M	Y	Minimize cost	Public transport integration; set partitioning; multi-echelon.
Deng et al. (2024) [87]	B&C	TDRP	MILP	1	1	Y	Minimize delay risk	Stochastic/robust; deadlines; energy constraints; multi-trip.
Lyu et al. (2025) [9]	B&P	PDP-mR-mD	MILP	M	M	Y	Minimize cost	Food delivery; transshipment; time windows; payload/battery.
Murray et al. (2020) [91]	B&B	mFSTSP	MILP	1	M	Y	Minimize makespan	Multi-drone; heterogeneous; multi-trip; endurance model.
Gao et al. (2023) [92]	CG	TDRP	MIP	M	M	Y	Minimize cost	Cooperative scheduling; energy model; rendezvous points.
Gao et al. (2023) [93]	B&C	MTDP-PDP	MILP	M	M	Y	Minimize makespan	Pickup delivery; multi-trip; heterogeneous drones.
Bruni et al. (2023) [94]	B&C	LRP under uncertainty	MILP	1	1	Y	Minimize latency	Energy model; multi-trip; robust optimization.

Notes: B&C=Branch and Cut; B&P=Branch and Price; B&B=Branch and Bound; CG=Column Generation. MILP=Mixed Integer Linear Programming; MIP=Mixed Integer Programming; MIQCP=Mixed Integer Quadratically Constrained Programming; CP=Constraint Programming. Problem types: TSP-MD=Traveling Salesman Problem with Multiple Drones; TDTL=Truck-Drone Team Logistics Problem; PDSTSP=Parallel Drone Scheduling Traveling Salesman Problem; LRP=Location-Routing Problem; TDRP=Truck-Drone Routing Problem; mFSTSP=multi-drone Flying Sidekick Traveling Salesman Problem. PDP mR mD denotes a pickup and delivery problem with multiple riders (couriers) and multiple drones, and MTDP-PDP denotes a multi-trip drone pickup and delivery problem. Symbols: M in “# Trucks”/“# Drones” denotes “multiple”. “Synchronization (Y/N)” indicates whether explicit truck-drone rendezvous/synchronization (temporal coupling) constraints are modeled (Y=yes; N=no). “Makespan” refers to the completion time of the overall delivery mission (maximum route completion time)

illustrates how lightweight construction heuristics can be coupled with operational and environmental accounting to support comparative assessments across delivery modalities. Building on such initial solutions, most state-of-the-art approaches rely on metaheuristics that repeatedly “destroy” a portion of the current plan and “repair” it under synchronization constraints. Adaptive large neighborhood search (ALNS) has become particularly prevalent, as adaptive operator selection helps balance exploration and exploitation under complex feasibility rules. Representative implementations demonstrate its effectiveness in urban routing settings with heterogeneous drones and realistic constraints such as time windows and transshipment coordination [9, 96].

Beyond ALNS, several metaheuristic families remain influential, mainly because they provide transparent control over intensification and diversification while accommodating problem-specific feasibility checks [97]. Iterated local search and variable neighborhood strategies are frequently adopted to handle multi-visit or multi-trip settings, where a single drone sortie may serve multiple customers and where feasibility depends on

load-dependent endurance models [70]. Time-dependent and uncertain travel conditions further motivate iterative re-optimization schemes that preserve feasibility while adapting the truck schedule and drone assignments as conditions evolve [98]. In dynamic or disruption-prone contexts (e.g., severe weather), rolling horizon metaheuristics embed a repeated re-planning mechanism into the search process, allowing the solution to remain feasible and responsive as new information arrives [99].

A smaller but increasingly visible thread concerns problem structures that introduce additional logical constraints beyond synchronization, such as precedence relations among tasks. In such cases, heuristic design must incorporate precedence-preserving moves and specialized repair operators to avoid generating infeasible solutions; recent work on precedence-constrained multi-truck multi-drone delivery highlights the importance of such constraint-aware neighbourhoods for both solution quality and computational stability [100]. Finally, metaheuristics bridge heuristic search and mathematical programming by solving restricted or decomposed subproblems within a metaheuristic loop, which is especially

useful when local improvements require solving tightly coupled assignment or scheduling components rather than simple swap/relocation moves [92].

Heuristics and metaheuristics are most effective when the instance size is large, the operational setting is rich (multi-trip, heterogeneous drones, time windows), and planners require high-quality solutions within limited computation time. Their main advantage lies in scalability and modeling flexibility: synchronization and endurance constraints can be enforced through tailored encodings and feasibility-preserving operators, and dynamic settings can be handled via rolling horizon re-optimization. However, performance evidence is often sensitive to design choices that are not standardized across studies, including energy models, rendezvous policies, operator sets, and parameter control strategies. Consequently, cross-paper comparisons should focus less on headline improvements and more on whether baselines, instance families, and feasibility assumptions are aligned. Overall, these methods form a practical “workhorse” layer for real-scale deployments, while their limitations in reproducibility and parameter dependence motivate hybrid and decomposition-assisted designs that provide stronger structure and more portable performance across

scenarios. Table 3 summarizes representative heuristic and metaheuristic algorithms from the literature.

3.4 Decomposition and hybrid algorithms

Decomposition and hybrid algorithms provide a structured route to scalability when truck–drone delivery models become too large or tightly coupled for direct monolithic optimization. The key idea is to exploit separability in decision layers. Typical separations include routing versus drone feasibility, facility or echelon decisions versus operational scheduling, and strategic plan selection versus detailed assignment and timing. By isolating these components, decomposition reduces the effective search space and enables stronger bounds or higher quality solutions than purely local search-driven heuristics on the full model.

A first major stream is Benders type decomposition, which partitions the problem into a master problem for high-level routing or design decisions and subproblems that check feasibility or generate recourse under synchronization, energy, and timing constraints. This structure is particularly common in robust or deadline-sensitive settings, where uncertainty makes direct mixed integer formulations difficult to solve at scale. For instance, decomposition-based designs have been used to manage

Table 3 Summary of heuristic and metaheuristic algorithms

Reference	Method Type	Core Strategy/Operators	Neighborhood/ Search Structure	Strengths & Limitations	Notes
Figliozzi (2020) [95]	Greedy	Insertion/removal operators	Nearest neighbor; cost saving	Fast initial solutions; sub-optimal for large instances	CO ₂ emissions; energy model; multi-drone.
Zhang et al. (2025) [96]	ALNS	Destroy repair; adaptive operators	2-opt, swap, relocation	Balances quality/time; parameter tuning needed	FSTSP; heterogeneous drones; urban routing.
Gu et al. (2023) [85]	Heuristic	Offline heuristic for MDP	Neighborhood search	Efficient for dynamic; suboptimal	On-demand pickups; multi-visit; time constraints.
Lyu et al. (2025) [9]	ALNS	Adaptive large neighborhood	Destroy repair, 2-opt	Scalable; good for large; tuning needed	Food delivery; transshipment; time windows.
Wang et al. (2022) [98]	Iterative Local Search	Local search with exchanges	Re-optimization, inter-pair swap	Efficient for time-dependent; suboptimal large	Time-dependent travel; uncertain traffic; multi-trip.
Murray et al. (2020) [91]	Heuristic	Sequence of subproblems	Insertion, relocation	Fast initial; limited optimality	Multi-drone; heterogeneous; endurance model.
Li et al. (2025) [99]	ALNS	R-ALNS under RH	Destroy repair, adaptive	Resilient to weather; dynamic; tuning needed	Hurricanes; pickup delivery; time dependent wind.
Gu et al. (2022) [70]	ILS-VND	Iterative local search with VND	Destroy repair, swap	Efficient; good quality; complex for large	Multi-visit; endurance model; time windows.
Gao et al. (2023) [93]	Matheuristic	Dynamic programming-based heuristic	Insertion, relocation	Fast; limited optimality	Pickup-delivery; multi-trip; heterogeneous drones.
Gao et al. (2023) [92]	Heuristic	Greedy with recourse	Nearest neighbor	Fast initial; suboptimal	Cooperative scheduling; energy model; rendezvous.
Tureci-Isik et al. (2025) [101]	VNS	VNS with acceleration	Swap, relocation	Efficient; good for stochastic; tuning needed	Stochastic; location routing; multi-trip.
Wu et al. (2022) [8]	SA+TS	SA+TS hybrid	Destroy repair, Tabu	Balances quality/time; parameter tuning	Contactless delivery; epidemic; multi-trip.

Notes: ALNS=Adaptive Large Neighborhood Search; ILS=Iterated Local Search; VNS/VND=Variable Neighborhood Search/Descent; SA/TS=Simulated Annealing/Tabu Search; RH=Rolling Horizon; MDP=Markov Decision Process; FSTSP=Flying Sidekick Traveling Salesman Problem; CO₂=carbon dioxide emissions (CO2). Operators: 2-opt=2-edge exchange; swap=exchange two visits; relocation=move a visit; destroy-repair=remove and reinsert neighborhood. Terms: “multi-trip” allows multiple drone sorties; “rendezvous” denotes truck–drone meeting/launch–retrieve coordination

delay risk objectives and stochastic/robust elements while maintaining tractable subproblem evaluations [87]. More generally, Benders style strategies are attractive when feasibility depends on complex drone endurance, synchronization, or scenario-specific constraints that can be assessed independently once the master decisions are fixed [102].

Complementary to Benders type designs, two-stage stochastic programming is well-suited when uncertainty affects both demand and operational feasibility. Dukanci (2026) [103] formulates an integrated location–routing truck–drone problem as a two-stage stochastic program with uncertain demand and drone travel time, and develops an exact scenario decomposition algorithm to solve the deterministic equivalent efficiently. This approach is particularly relevant for facility-integrated settings because it explicitly captures how uncertainty links strategic location choices with second-stage routing and drone sortie feasibility.

A second stream relies on set partitioning and column generation. In these frameworks, the master problem selects a combination of routes or route fragments from a (potentially very large) pool, while the pricing subproblem generates promising new columns guided by reduced costs. This paradigm is especially effective for multi-echelon or multi-modal systems in which the “route” is naturally defined as a composite service pattern, such as integrating public transport legs with truck and drone operations [90]. Column generation has also been combined with problem-specific heuristics to accelerate convergence and handle large-scale instances, particularly in operational contexts with transshipment, time windows, and coordinated multi-agent delivery [9].

Hybridization often occurs because neither exact decomposition nor standalone metaheuristics fully address real-world complexity. A common practice is to embed metaheuristics inside decomposition loops (or vice versa). Logic-based Benders decomposition is frequently adopted when subproblems are more naturally treated as scheduling or assignment problems rather than linear programs, allowing tailored feasibility checks and dynamic programming components to be integrated into a mathematically grounded structure [92, 93]. Rolling horizon hybridization is another recurring pattern for dynamic or disruption-prone operations: the planning horizon is repeatedly updated, while each replanning step can use a mixture of exact subproblem solving and heuristic guidance to maintain responsiveness and feasibility under changing information [99]. Finally, hybrid designs also appear in time-indexed scheduling settings, where battery management and operational timing constraints create large time-expanded models and motivate specialised heuristic–exact combinations for tractable drone scheduling decisions [84].

Decomposition and hybrid algorithms are most effective when the problem exhibits a clear multi-layer structure (e.g., multi-echelon, facility integration, scheduling–routing coupling) or when uncertainty and operational realism make monolithic models impractical. Their main advantage is that they translate “complexity” into modular subproblems that can be strengthened with cuts, columns, or tailored dynamic programming, often yielding more portable performance than heavily parameter-tuned metaheuristics. The main limitations lie in implementation complexity and comparability: performance depends on the master–subproblem interface (cut design, column definition, stabilization) and on modeling choices that vary across studies (energy models, synchronization rules, discretization). For reproducible and interpretable advances, it is therefore important to report not only aggregate objective improvements, but also decomposition architecture, subproblem definitions, and the conditions under which convergence and computational stability are achieved.

Table 4 organizes representative decomposition and hybrid approaches from the literature, clarifying how they partition decision components, coordinate subproblems, and integrate heterogeneous solution mechanisms.

3.5 Learning-based and multi-agent algorithms

Learning-based and data-driven algorithms have emerged as a complementary paradigm for truck–drone cooperative delivery, especially in operational settings that require repeated replanning under uncertainty, disruptions, or complex multi-agent interactions. Rather than solving a full optimization model at every decision epoch, these approaches learn decision policies that map observed system states, such as vehicle positions, remaining battery, traffic conditions, and realized requests, to actions including dispatching, task assignment, rendezvous selection, and replanning triggers. Their main appeal is adaptivity: once trained, policies can respond quickly to newly revealed information without repeatedly solving large-scale optimization models. However, this advantage comes with a central methodological difficulty: feasibility cannot be assumed to emerge automatically from policy learning, because synchronization, battery endurance, charging logic, and airspace restrictions remain hard operational constraints.

From a sequential decision perspective, several studies formulate truck–drone operations as Markov decision processes or approximate dynamic programs in order to address stochastic demand and travel-time uncertainty. For example, van Steenberg et al. (2023) [105] develop a sequential decision framework for truck–UAV coordination under stochastic travel times by combining approximate value and policy function representations with heuristic search, and report substantial reductions

Table 4 Summary of decomposition and hybrid algorithms

Reference	Method Category	Decomposition Structure	Subproblem Types	Hybrid Components	Strengths & Limitations
Colajanni et al. (2023) [102]	Decomposition	Benders	Truck routing, drone feasibility	MIP + heuristic	Scalable; convergence issues for large.
Boccia et al. (2024) [29]	Hybrid	Logic-based Benders	Drone sortie, truck synchronization	MIP + matheuristic	Robust; tuning for neighborhoods.
Liu et al. (2026) [84]	Hybrid	Time indexed	Battery check, scheduling	VNS + endurance heuristic	Good for dynamic; data dependency.
Delle Donne et al. (2025) [90]	Decomposition	Set partitioning	Multi-echelon routing	CG + MIP	Scalable; large graphs slow.
Wang et al. (2019) [61]	Hybrid	Marginal cost	Independent/carried coordination	NN + Tabu	Efficient; avoids local optima.
Liu et al. (2021) [104]	Hybrid	Two stage	Echelon separation	DP + SA/Tabu	Good for two-echelon; tuning needed.
Deng et al. (2024) [87]	Decomposition	Benders	Delay risk minimization, routing	BD + SAA/RO	Robust to uncertainty; convergence for stochastic.
Murray et al. (2020) [91]	Hybrid	Subproblem sequence	Drone assignment, routing	MILP + heuristic	Practical for multi-drone; suboptimal for large.
Li et al. (2025) [99]	Hybrid	Rolling horizon	Dynamic PDP, weather adaptation	ALNS + RH	Resilient to uncertainty; dynamic handling.
Gao et al. (2023) [92]	Hybrid	Benders with DP	Scheduling, routing	CG + LBBD + DP	Efficient for cooperative; convergence issues.
Gao et al. (2023) [93]	Hybrid	Logic-based Benders	Pickup delivery, multi-trip	LBBD + DP	Scalable; complex subproblems.

Notes: BD=Benders Decomposition; LBBD=Logic Based Benders Decomposition; CG=Column Generation; DP=Dynamic Programming; SAA=Sample Average Approximation; RO=Robust Optimization

in lateness in disaster-oriented case studies. In related data-driven settings, online planning may also be supported by look-ahead simulation and learned prioritization rules, which aim to improve service outcomes relative to myopic decision rules under dynamic demand arrivals [106]. These studies illustrate the value of learning when decisions must be revised repeatedly as uncertainty unfolds over time.

When multi-agent interaction and nonstationarity become dominant, deep reinforcement learning (DRL) and multi-agent DRL are increasingly used to learn coordination policies without explicitly modeling every recourse action. A representative example is given by Peng et al. (2025) [80], who formulate truck–drone emergency coordination as a Markov game and apply multi-agent DRL in a setting with dynamically updated incident locations and resource demands. More broadly, learning-based approaches have also been explored in disruption-driven urban logistics, where rapid coordination adjustment is required under changing operational conditions [8]. Yet these methods differ substantially in how feasibility is maintained. Existing studies rely on infeasible-action masking, rule-based repair operators, reward shaping with penalty terms, or hybrid architectures in which optimization or heuristic modules remain responsible for final feasibility enforcement. This distinction is important because reported adaptive performance may reflect very different balances between learned decision quality and externally enforced operational feasibility.

To reconcile adaptivity with constraint satisfaction, an increasing number of studies integrate learning with optimization or heuristic search. In such hybrid designs, structured routing and scheduling modules provide feasibility control, while learning is used to guide operator selection, action prioritization, or policy refinement. For example, multi-agent DRL has been combined with graph-based representations and tailored reward structures to support charging-aware coordination under spatiotemporal dependencies, with benchmarking against heuristic and evolutionary baselines to validate performance gains [107]. These developments suggest that learning-based methods are often most effective when they augment, rather than replace, constraint-aware optimization components.

Despite their promise, learning-based methods face two major challenges beyond feasibility preservation. The first is generalization. Many reported results are obtained in narrowly specified simulation environments with fixed network layouts, demand processes, fleet compositions, or disruption patterns, making it unclear how well trained policies transfer across cities, customer distributions, synchronization rules, or uncertainty regimes. This concern is especially important in multi-agent settings, where policy quality can be highly sensitive to environment design and coordination structure. The second challenge is training cost and stability. Sample inefficiency, reward sensitivity, action-space complexity, and nonstationarity in MARL can make training

computationally expensive and difficult to reproduce, even when inference is fast after training.

Accordingly, the empirical assessment of learning-based methods should go beyond mean objective improvements alone. Because training environments, state and action definitions, reward design, and feasibility-enforcement strategies vary substantially across studies, direct comparison of reported gains is often difficult. When feasibility is maintained through action masks, repair operators, or embedded optimization modules, reported performance should be interpreted as the outcome of a hybrid decision system rather than of the learned policy alone. More informative evaluation should therefore include matched simulation settings, strong optimization or heuristic baselines, out-of-sample testing, feasibility rates, service-reliability indicators, and transparent reporting of computational budgets for both training and inference. Overall, learning-based approaches are most compelling in truck–drone systems when fast adaptive responses are needed under uncertainty, but their value should be judged not only by nominal performance gains, but also by how feasibility is enforced, how robustly policies generalize, and how rigorously they are evaluated.

Table 5 provides a structured overview of representative learning-based and multi-agent approaches, highlighting their learning paradigms, model architectures, and the state–action representations that underpin their decision-making behaviours.

3.6 Scalability, complexity, and algorithmic trends

Scalability has become a defining challenge in UAV–vehicle cooperative delivery as problem instances move from stylized benchmarks to operationally realistic settings. Even moderate increases in the number of customers, UAVs, facilities, or time discretization granularity can trigger a disproportionate expansion of the decision

space, because routing choices and synchronization schedules are tightly interdependent. Classical formulations such as the flying sidekick problem and TSP-D already embed coupled timing, sequencing, and endurance constraints. As a result, exact methods typically remain limited to small or medium instances. This tractability issue is repeatedly identified as a practical bottleneck in humanitarian and emergency applications [21, 43, 110].

The computational burden is not driven by size alone, but by several interacting structural sources of complexity. First, synchronization constraints couple truck movements and UAV sorties across time, introducing strong combinatorial dependencies that become more pronounced under congestion, travel time variability, or deadline-driven service targets. Second, energy feasibility adds another layer of coupling by linking sortie decisions to load-dependent and potentially time-varying battery consumption, which complicates both pricing and neighborhood evaluation. Yin et al. (2023) [83], for example, show that robustness against uncertain demand and travel times can significantly increase computational effort, as uncertainty must be propagated through synchronization and feasibility checks. Third, facility-supported and two echelon designs introduce additional decision layers, including hub selection, replenishment or battery logistics, and cross-layer coordination, which expand both the feasible region and the evaluation complexity of candidate solutions [41, 111].

These complexity drivers have shaped a clear set of algorithmic trends. When the model exhibits separable decision layers, decomposition-oriented designs are increasingly adopted to isolate routing from sortie generation, scheduling, or facility decisions, thereby improving tractability while preserving structural interpretability [13, 81]. For large deterministic instances, metaheuristics and hybrid heuristics remain the primary workhorse,

Table 5 Summary of learning-based and multi-agent algorithms

Reference	Learning Framework	Model Architecture	State–Action Design	Training Setting	Strengths & Limitations
Betti Sorbelli et al. (2023) [22]	RL	NN	Drone energy, wind direction, truck position trajectory choice	Simulation-based; offline	Handles uncertainty; training time high.
Torabi et al. (2025) [108]	MARL	Graph NN	Coverage state, vessel/drone position routing action	Offline; dynamic demand	Generalization good; Explanatory low.
Bai et al. (2025) [109]	DQN	CNN/LSTM	Precedence, truck/drone state assignment	Simulation; online	Robust to precedence; data dependency.
She et al. (2024) [100]	Transformer-RL	Transformer	Aerial congestion, energy routing decision	Simulation-based; dynamic	Real-time adaptation; high training cost.
Wang et al. (2019) [61]	PPO	MLP	Independent/carried coordination, energy scheduling	Offline; multi-agent	Scalable; limited generalization.
Peng et al. (2025) [80]	MADRL	NN	Truck–drone state, emergency routing action	Simulation-based; multi-agent	Handles dynamic; training cost.
Qiu et al. (2025) [107]	R-TEA MADRL	Relational GCN	Truck–drone state, charging routing/charging action	Simulation-based; multi-agent	Handles charging; trajectory entropy exploration.

because they can explore large neighborhoods efficiently and incorporate feasibility-preserving operators for multi-UAV and high demand settings [112, 113]. In dynamic and uncertain environments, learning-based and multi-agent reinforcement learning methods are being explored to support rapid replanning, especially when repeated optimization becomes computationally prohibitive, and decision policies must adapt online [30, 105, 114].

Scalability in truck–drone systems is primarily constrained by synchronization and energy feasibility coupling, and this constraint is further amplified by uncertainty and facility/echelon integration. Accordingly, the field is moving toward architectures that combine complementary strengths: decomposition for structural tractability, metaheuristics for large-scale search under rich feasibility rules, and learning-based components for rapid adaptation under nonstationarity. A key methodological implication is that future progress should be evaluated not only by objective improvements, but also by computational stability, portability across modeling

assumptions, and transparency of feasibility enforcement in realistic large-scale settings.

Table 6 provides a paradigm-level synthesis of the solution methodologies reviewed in Sect. 2.1.1. It contrasts how studies report performance evidence, including provable bounds or optimality gaps when available, time budgeted best or average solution quality under fixed runtimes, and reliability-oriented indicators such as feasibility rates, deadline compliance, and tail lateness under uncertainty or disruptions.

4 Applications and empirical findings

The practical value of UAV–vehicle cooperative delivery emerges most clearly when models and algorithms are examined in concrete application settings. Empirical studies based on synthetic networks, real-world maps, operational data, and field experiments illustrate how system configurations, demand characteristics, energy constraints, and regulatory conditions jointly influence performance across different environments. Section 2.1.1 synthesizes these application-oriented findings by considering not only what each application stream reports,

Table 6 Paradigm level synthesis of solution methodologies, evidence, and scalability

Paradigm	Typical problem families	Evidence & evaluation practice	Strengths	Dominant bottlenecks	Reproducibility/comparability	Best fit conditions
Exact (B&C/B&P/CG; MILP/MIP)	TSP/VRP with truck–drone synchronization; scheduling; energy/endurance; facility layers	Optimality proofs or bounds; gaps when available; runtime and sensitivity tests	Benchmark reference; isolates synchronization and feasibility effects	Time expanded synchronization; multi-trip/multi-drone coupling; pricing and dominance complexity	Highly sensitive to energy models, rendezvous rules, and discretization; solver settings matter	Moderate scale; benchmarking and validation of other paradigms
Heuristic/Metaheuristic (ALNS, VNS/ILS, SA/TS, GRASP)	Large-scale routing with constraints; multi-visit/PD; time-dependent settings	Best/avg objective under time budgets; baseline comparisons; scenario tests	Scalable; flexible constraint integration; fast re-optimization	Operator design and tuning; feasibility checks can dominate; instance-specific behaviour	Requires consistent benchmarks and stopping rules; parameter disclosure critical	Large instances; latency-constrained planning; frequent re-optimization
Decomposition/Hybrid (Benders/LBBD, DW/CG, set partitioning + search/DP)	Multi-echelon and facility integrated systems; routing–scheduling coupling	Bounds + heuristic completion; convergence behavior; runtime and objective quality	Exploits structure; scalable for integrated models; systematic search	Weak relaxations; slow pricing/cut management; high implementation complexity	Needs clear master–subproblem interfaces and feasibility enforcement details	Structured large instances; when both scalability and rigor are required
Learning-based/Multi-agent (RL/MARL; learning + optimization)	Online/dynamic dispatch; stochastic travel times/demand; emergency response	Out-of-sample simulation; service level and tail metrics; robustness tests	Adaptive under nonstationarity; handles large state/action spaces	Constraint satisfaction and safety; generalization under shift; training stability	Fair comparison needs identical environments and metrics; protocol transparency essential	High uncertainty, frequent replanning; best with feasibility preserving layers

but also how far the reported findings can be compared across assumptions. Directly reported outcomes, such as cost savings, profit gains, lateness reductions, waiting-time reductions, optimality gaps, and energy impacts, are interpreted together with the synchronization rules, energy models, uncertainty settings, and benchmark structures under which they were obtained. The section first reviews urban parcel logistics, then examines medical, emergency, and humanitarian operations, food

and on-demand delivery, and case-based benchmark evidence.

To organize this diverse literature, Table 7 summarizes representative application scenarios, distinguishing scenario categories, key drivers for UAV–vehicle cooperation, primary problem focus, and dominant operational constraints. The full version of Table 7 is provided in Appendix Table A.

Table 7 Overview of application scenarios and key modeling elements

Reference	Scenario Category	Scenario Drivers	Problem Focus	Key Constraints	Scenario Specific Elements
Gu et al. (2023) [85]	Food and On-Demand Delivery	E-commerce growth; surge in on-demand logistics demands; peak hour service reliability	How to dynamically adjust truck-drone routing to maximize profits	Deadlines; maximum working hours; drone load/endurance limits; uncertain pickup requests	Scheduled deliveries combined with dynamic pickups; drone multi-request/trip; uncertain request acceptance rate
Lyu et al. (2025) [9]	Food and On-Demand Delivery	Urban density growth; smartphone apps; food delivery market expansion; rider shortages	How to coordinate multi-riders/multi-drones to minimize costs in one-to-one pickup delivery	Time windows; load capacity; battery endurance; location accessibility; synchronisation transshipment	Docking hub transshipment; rider/drone independent/cooperative; branch and price with ALNS; large-scale instances
Liu et al. (2025) [84]	Food and On-Demand Delivery	On-demand meal delivery; time pressure; battery management	How to schedule drones with optimized battery replacement	Load-dependent energy; battery replacement time; drone downtime	MIP model; time expanded network; hybrid VNS; on-time delivery improvements; battery strategy benefits
van Steenberg et al. (2023) [105]	Medical, Emergency, and Humanitarian Response	Post disaster relief; travel uncertainties; UAV integration	How to route trucks-UAVs with stochastic times min penalties	Time windows; UAV range; uncertainties	SDP; RL (VFA/PFA); heuristics; Nepal/Indonesia cases; lateness reductions 85%
Tureci-Isik et al. (2025) [101]	Medical, Emergency, and Humanitarian Response	Post-disaster response; network disruptions; uncertain access	How to locate depots/route parallel truck-drones under stochastic disruptions	Uncertain road disruptions; capacities; time windows; parallel ops	Two-stage stochastic MIP; VNS heuristic; Van Earthquake case; uncertainty benefits
Wang et al. (2022) [98]	Medical, Emergency, and Humanitarian Response	Urban congestion; peak hour uncertain traffic; timely medical/on-demand needs	How to coordinate truck-drone under time-dependent travel times to minimize costs	Time-dependent road travel times; uncertain traffic; drone speed/load; synchronization	Chongqing traffic data case; road network congestion states; iterative local search; terrain overcoming
Peng et al. (2025) [80]	Medical, Emergency, and Humanitarian Response	Emergency disaster response; dynamic affected areas updates; resource delivery uncertainties	How to collaboratively route truck-drone tandems with dynamic emergency responses	Dynamic node updates; drone launch/return synchronization; relief resource capacities	Markov game model; multi-agent DRL with prioritized replay/invalid masking; Wenchuan earthquake case; truck-drone vs. truck/helicopter
Deng et al. (2024) [87]	Urban Last Mile and Parcel Logistics	Rapid e-commerce development; uncertain travel times causing delays; time-definite delivery demands	How to minimize service delay risks under uncertainty	Deadlines; uncertain travel times; drone battery/load; synchronization rendezvous	Big/small dataset handling; stochastic/robust optimization; Benders decomposition algorithm
Murray & Raj (2020) [91]	Urban Last Mile and Parcel Logistics	Last mile parcel delivery; geographically dispersed customers; minimize completion time	How to coordinate truck with heterogeneous drone fleet for minimal time delivery	Drone endurance/load; single delivery/drone; rendezvous points; automated launch/retrieval	Heterogeneous drones; endurance model impacts; diminishing marginal returns; MILP with sequential subproblem heuristic
Gu et al. (2022) [70]	Urban Last Mile and Parcel Logistics	Drone delivery potential; complex synchronization; multi-visits/endurance models	How to evaluate solutions hierarchically for VRPD with multi-visits	Drone payload/flight time endurance; multi-customers/trip; synchronization	Hierarchical evaluation method; ILS-VND hybrid; multi-visit TSPD benchmarks; drone tech impacts
Zhang et al. (2025) [96]	Urban Last Mile and Parcel Logistics	E-commerce growth; last mile challenges; urban/sub-urban freight; sustainability	How to optimize truck-drone routing with parking lots in urban networks	Drone endurance; truck parking; speed ratios; carbon efficiency	Heuristics; real urban networks (5 cities); customer aggregation; speed ratio sensitivity; time/carbon savings

4.1 Urban parcel Logistics

Urban parcel logistics remains the most extensively studied application of UAV–vehicle cooperative delivery. The central question is not simply whether truck–UAV coordination can improve performance, but under what urban operating conditions these gains remain substantial once congestion, time sensitivity, synchronization, and energy feasibility are explicitly accounted for. Early formulations such as the flying sidekick traveling salesman problem and related truck–UAV traveling salesman variants [115] established the basic coordination logic by showing that UAV sorties can serve off-route customers and thereby reduce truck detours. Murray and Chu (2015) [51] introduced the FSTSP with explicit truck–UAV synchronization, while Agatz et al. (2018) [62] extended this line to the TSP-D and demonstrated how exact and heuristic methods could be used to minimize completion time under coordinated truck–drone operations.

Subsequent studies generalized these foundations to multi-UAV and multi-truck settings in order to better reflect metropolitan delivery requirements [28]. A recurring empirical pattern is that the benefit of adding UAV capacity is positive but not proportional: additional drones do not guarantee commensurate system-level gains. Instead, the realized improvement depends on customer spatial dispersion, service-time structure, UAV eligibility, and the efficiency of launch, recovery, and rendezvous operations. In this sense, truck–UAV cooperation improves performance most clearly when aerial service reduces truck detours without generating excessive waiting or idle synchronization time.

More recent urban studies provide stronger quantitative evidence on these comparative effects. In tactical fleet and facility planning, Rave et al. (2023) [78] found that a mixed system combining truck-launched drones and dedicated drone stations was optimal in 58% of the tested scenarios, yielding average cost savings of 33.3% relative to a truck-only system and 14.1% relative to a system with trucks and truck-launched drones only. In dynamic urban operations with random requests and en-route synchronization, Cui et al. (2024) [82] reported that their reinforcement learning framework increased total profit by an average of 28.03% over benchmark methods, while en-route takeoff-and-landing coordination outperformed more restrictive benchmark settings by 8.43% in multi-day instances and reduced waiting by 0.9h/(drone-day) on average. These results indicate that the gains of truck–UAV cooperation are substantial, but they are highly conditioned by coordination design rather than arising automatically from the mere presence of drones.

At the same time, the same literature shows that these gains narrow once energy feasibility and operational realism are modeled more explicitly. Urban parcel systems

are especially sensitive to payload variation, wind, and short-range battery constraints, because many seemingly attractive sorties become fragile when detailed flight feasibility is imposed. Studies incorporating payload-dependent energy consumption, no-fly zones, and wind effects [66, 77] show that mission feasibility screening and conservative energy buffers are often necessary for reliable performance. From a comparative perspective, this means that nominal improvements in route time or cost should be interpreted cautiously when studies differ in whether they explicitly model battery consumption, payload-energy coupling, or detailed airspace constraints. Likewise, comparative analyses against truck-only delivery [38] suggest that sustainability and cost advantages are possible, but they depend on routing structure, rendezvous efficiency, and the proportion of customers that can be served feasibly by UAVs.

Facility-supported and two-echelon designs further broaden the urban parcel paradigm by coupling truck–UAV operations with micro-depots, lockers, or drone stations [81, 112]. The comparative evidence suggests that these configurations can expand effective UAV coverage and reduce truck travel, especially under curb-access restrictions or dispersed demand patterns. However, their benefit is not monotonic. Once transshipment, handling, and synchronization overheads are internalized, the marginal advantage of additional facilities tends to diminish. A similar caution applies to scheduling-focused and tandem routing formulations [52, 116], which show that the operational value of UAV assistance depends not only on flight capability but also on how well drone timing is aligned with truck movement.

Empirically, truck–UAV cooperation tends to perform best in settings with moderate-to-high spatial dispersion, sufficient UAV-eligible demand, and coordination mechanisms that reduce both truck detours and synchronization waiting. By contrast, the reported advantages become smaller or more fragile when detailed energy feasibility, battery limits, no-fly constraints, or facility-handling overheads are incorporated. Interpretively, this indicates that the key determinant of performance is not UAV adoption itself, but whether the coordination structure can convert aerial flexibility into net system-level gains after waiting, energy, and operational overheads are fully considered. For this reason, evidence from urban parcel studies should distinguish clearly between direct empirical outcomes, such as cost, profit, or waiting-time reductions, and broader interpretive claims about sustainability or scalability, which remain conditional on modeling assumptions and evaluation settings. Recent work has also strengthened benchmarking in urban-relevant VRP-D settings through improved exact and hybrid optimization approaches [117, 118], while learning-based models increasingly target urban variability and online

adjustment [24, 114]. However, these advances do not remove the need for careful cross-study comparison under aligned operational assumptions.

4.2 Medical, emergency, and humanitarian response

Medical, emergency, and humanitarian response constitutes a distinct and highly consequential application domain for UAV–vehicle cooperative delivery. Compared with urban parcel logistics, these missions are more strongly shaped by time-critical service requirements, disrupted or partially inaccessible transport infrastructure, and severe uncertainty in demand, travel conditions, and operational feasibility [119]. As a result, the central issue is not merely how to reduce mean travel time or operating cost, but how to maintain timely and reliable service under degraded and evolving conditions [71].

A major line of work has therefore developed stochastic, robust, or uncertainty-aware coordination models [60]. These studies explicitly recognize that nominally feasible truck–UAV plans may fail once post-disaster travel times, demand levels, or access conditions deviate from expectations. In this literature, evaluation is typically shifted away from average cost alone toward deadline compliance, mission success, and lateness-related risk. Robust models such as Yin et al. (2023) [83] show that uncertainty in demand and truck travel time must be incorporated directly if delivery plans are to remain feasible with high probability after disruption. Their formulation also makes clear that the relevant trade-off is not simply cost minimization, but cost versus worst-case tardiness under bounded uncertainty. More broadly, this stream indicates that deterministic or nominal solutions may appear efficient *ex ante*, yet become fragile once uncertainty is explicitly internalized.

Existing empirical evidence also suggests that the value of truck–UAV cooperation in humanitarian settings depends heavily on how uncertainty affects accessibility and information quality. In post-disaster network assessment, Zhang et al. (2021) [72] develop a collaborative truck-and-drone system to maximize the value of information collected within a fixed assessment horizon. Their computational results show that the proposed algorithm achieves average optimality gaps below 10% for terminated instances, while the real-case analysis in Istanbul indicates that system performance is much more sensitive to drone speed than to battery endurance, and that longer assessment windows yield additional informational value with diminishing marginal returns. This is an important contrast to parcel-delivery logic: in humanitarian assessment, the benefit of drone assistance often lies not only in direct delivery speed, but in improving situational awareness and supporting more precise downstream relief decisions.

A second comparative pattern concerns dynamic adaptation. Static synchronization plans can quickly lose value when incident locations change, road accessibility is updated, or affected areas emerge sequentially over time. To address this, recent studies allow real-time revision of launch timing, rendezvous decisions, and service priorities. Van Steenbergen et al. (2023) [105], for example, show in Nepal and Indonesia case settings that adaptive decision policies under travel-time uncertainty can reduce lateness substantially, with the improvements in the reviewed literature reaching about 85% in the reported cases. These results suggest that the value of adaptive or learning-based methods is most evident when information updates are frequent enough, and the operational environment changes quickly enough, that repeated exact replanning is no longer practical.

At the same time, adaptivity and robustness are not costless. Frequent replanning can introduce coordination overhead, repeated rendezvous adjustments, and additional waiting, while robust formulations may become conservative if uncertainty sets are too wide. For this reason, the key comparison in this application domain is not simply static versus dynamic or deterministic versus robust, but which modelling framework is most appropriate under a given level of information availability and operational volatility. In particular, stochastic models are more informative when probability data are sufficiently rich, whereas robust models are often more suitable when only partial or interval-type information is available [71, 83]. The same caution applies to feasibility safeguards such as conservative flight-time buffers or backup synchronization choices: these mechanisms improve resilience, but may reduce nominal efficiency.

4.3 Food and on-demand delivery

Food and on-demand delivery represents a distinct application domain for truck–UAV cooperation because service value is strongly shaped by short decision cycles, pronounced peak demand, and high sensitivity to delay. Compared with conventional parcel logistics, these systems typically operate under tighter temporal budgets, more volatile demand arrivals, and shorter effective planning horizons. As a result, the central issue is not only whether UAV support can accelerate service, but whether rapid aerial dispatch can remain feasible and responsive once battery turnaround, synchronization, and repeated replanning are explicitly considered [69].

A key operational feature of this literature is the coupling between battery-constrained scheduling and high-frequency service [120]. Because sorties are short and repeated frequently, battery replacement, charging, and recovery time can become binding constraints rather than secondary operational details. Kumbhani et al. (2026) [11] examine drone adoption in sustainable urban

food delivery under practical operating assumptions and quantify both economic and environmental impacts. Liu et al. (2025) [84] further show in on-demand meal delivery that battery replacement decisions materially affect the feasibility and reliability of short-cycle operations. Taken together, these studies suggest that the operational value of UAV assistance in food delivery depends not only on flight speed, but also on whether battery turnover can support rapid dispatch without eroding system slack.

A second recurring comparative pattern concerns synchronization efficiency. In hybrid truck–drone systems for meal or instant delivery, UAVs are typically used for urgent or delay-sensitive dispatches, while trucks provide batching, inventory support, or replenishment. Under such settings, UAV support can reduce waiting time in congested districts by bypassing ground traffic, but the magnitude of this benefit depends heavily on launch timing, rendezvous design, and recovery coordination. Poor synchronization can generate truck idling or UAV waiting at recovery points, thereby offsetting the speed advantage of aerial service. Zhu et al. (2025) [121], for example, show in green truck–drone route optimization with demand distribution and multi-drop settings that waiting and rendezvous management become limiting factors when the system operates close to capacity. This indicates that responsiveness gains in on-demand settings should be interpreted as coordination-dependent rather than as automatic consequences of UAV deployment.

Dynamic and rolling decision processes are therefore central in this domain. Because lunch and dinner peaks, online arrivals, and fluctuating service priorities can quickly invalidate static plans, many recent models update launch timing, task assignment, and rendezvous choices as new information is revealed [122]. Gu et al. (2023) [85] develop a dynamic truck–drone routing problem for scheduled deliveries and on-demand pickups with time-related constraints, showing how dynamic request integration affects both profitability and operational feasibility. Zhen et al. (2025) [123] likewise study on-demand delivery with trucks carrying drones and develop exact solution methods to minimize operating cost while improving responsiveness for time-sensitive service. Learning-based approaches are also increasingly explored for such volatile settings. Xiang et al. (2025) [114] propose a reinforcement framework with a transformer-based model for dynamic urban drone delivery and report improved reactivity under demand volatility. However, these results should be interpreted primarily as evidence of methodological potential for online adjustment, rather than as directly comparable performance evidence across all food-delivery settings.

Another important feature of food and on-demand delivery is that payload and quality sensitivity interact with time pressure. Many food orders are lightweight and

physically compatible with UAV payload limits, which increases UAV eligibility relative to some parcel applications. At the same time, service quality deteriorates rapidly with delay, effectively tightening the delivery time window. Cooperative designs can therefore allocate urgent final-stage dispatches to UAVs while maintaining consolidated inventory and replenishment on ground vehicles. Li et al. (2025) [10] analyze collaborative drone-and-rider food delivery and provide quantitative evidence that task allocation structure materially influences cost and operational performance in time-critical delivery. More broadly, formulations with explicit time windows and lateness penalties show that outcomes depend strongly on how service reliability is weighted relative to operating cost. Although developed in a parcel-delivery context, studies such as Fu et al. (2025) [14] illustrate a broader evaluation principle that is also relevant here: average cost alone is insufficient when delay sensitivity is central to system performance.

In summary, truck–UAV cooperation tends to be most beneficial in settings with dense peak demand, severe ground congestion, and sufficient volumes of lightweight, delay-sensitive orders. By contrast, the reported gains weaken when battery turnaround, rendezvous waiting, or replanning overhead absorbs a substantial share of the short service-time budget. This means that the main trade-off in this domain is not simply speed versus cost, but responsiveness versus operational slack under tight temporal constraints. Accordingly, evidence in food and on-demand delivery should report not only mean cost or mean travel time, but also deadline violation rates, peak-period service reliability, and tail-delay indicators such as worst-case or high-quantile lateness, so that comparative conclusions reflect the actual value of timely service.

4.4 Case studies and benchmark insights

Case studies and benchmark analyses provide the most direct evidence on the external validity of truck–UAV cooperative delivery models. Compared with stylized computational experiments, they clarify whether the gains reported in routing and scheduling studies remain meaningful once real geographic layouts, observed travel conditions, facility constraints, and operational frictions are taken into account. In this sense, the central question is not only whether a given coordination strategy performs well on its own instances, but whether its reported advantages remain informative across different spatial structures, operational assumptions, and evaluation settings.

A first comparative pattern concerns spatial context. Existing case-based studies consistently show that the benefit of truck–UAV cooperation is strongly mediated by the geometry of the service area, road-network structure, and the asymmetry between ground and aerial

movement. Early experiments on road-network instances already indicated that coordinated truck–UAV routing can reduce truck detours and improve service efficiency when off-route customers are sufficiently UAV-eligible [51, 62]. Subsequent case-oriented work further shows that this advantage is not uniform across environments. In rural last-mile delivery with steep roads, for example, Xiao et al. [113] show that the relative value of aerial dispatch changes substantially because road-based travel becomes highly asymmetric, thereby altering both the effective service radius of trucks and the coordination value of drones. More broadly, these studies suggest that spatial separation and network asymmetry are key pre-conditions for realizing substantial cooperative gains.

A second comparative pattern concerns infrastructure support and operational realism. Facility-supported designs extend the feasible service region by adding micro-depots, lockers, or drone stations, and thereby make truck–UAV cooperation less dependent on direct truck launching alone [78]. Empirical evidence indicates that such facilities can reduce truck travel and shorten UAV sorties, particularly where curb access is limited or local road conditions hinder direct vehicle service. However, the same literature also shows that the gains are not monotonic. Once transshipment, handling, and synchronization overheads are internalized, the marginal benefit of higher facility density begins to diminish [81]. This finding is important because it reveals a broader benchmarking lesson: performance gains observed in simplified network settings may shrink when case studies account more explicitly for handling times, launch/recovery constraints, and real-map operational frictions.

Temporal variability forms a third determinant of comparative performance. Studies evaluating rolling-horizon or online coordination under time-varying demand show that adaptive launch, assignment, and rendezvous decisions can improve responsiveness when demand surges are short-lived or requests arrive stochastically [82, 85]. At the same time, this evidence also points to a clear boundary condition. Frequent replanning introduces coordination overhead, repeated synchronization adjustments, and potential waiting losses, so the net gain depends on whether the rate of state change is high enough to justify dynamic adaptation. In other words, dynamic coordination is most valuable not simply because the system is uncertain, but because the operational environment changes quickly enough that static or infrequently updated plans lose relevance before execution is completed.

Large-scale benchmark experiments further suggest that methodological performance is often shaped by solvable problem scale and feasibility enforcement, rather than by objective value alone. In multi-UAV, multi-echelon, or dynamic settings, many studies rely on hybrid

frameworks that combine optimization-based feasibility control with heuristics or policy-learning components in order to manage large action spaces and dense synchronization decisions [80]. A method that performs well on a larger, more realistic problem class is not directly comparable to one reporting stronger objective values on a smaller or more stylized benchmark. Thus, benchmark interpretation should distinguish between improvements due to better coordination quality and improvements due to differences in instance difficulty, modelling detail, or feasibility screening rules.

Taken together, case studies and benchmark analyses support two broad comparative conclusions. Empirically, truck–UAV cooperative delivery can generate meaningful gains in travel efficiency, responsiveness, or coverage, but these gains are highly contingent on spatial structure, infrastructure support, synchronization design, and the realism of operational constraints. Across application domains, the benefits are strongest when aerial service reduces ground detours, improves access to time-sensitive or hard-to-reach locations, and does not create excessive synchronization waiting. However, the magnitude of these benefits remains highly assumption-dependent: energy feasibility, UAV-eligible demand, facility-handling costs, uncertainty treatment, and benchmark design can all change the interpretation of reported gains. For cumulative progress, performance improvements should therefore be read as context-specific evidence rather than as universal claims about truck–UAV cooperation.

5 Challenges in UAV–vehicle cooperative delivery

Despite sustained progress in modeling and solution methods, UAV-vehicle cooperative delivery systems continue to face barriers that limit their routine deployment. These challenges arise from two sources. One is the inherent difficulty of coordinating heterogeneous agents, including trucks, UAVs, and supporting facilities, under tightly coupled spatial and temporal constraints. The other is the gap between stylized assumptions and operational realities, such as travel time variability, condition-dependent energy consumption, and fragmented airspace governance. This section discusses the main challenges from modeling, operational, regulatory, and sustainability perspectives.

5.1 Modeling challenges

From a modeling perspective, UAV vehicle cooperative delivery differs from classical vehicle routing because aerial sorties create tight coupling across time, space, and energy. One core difficulty is spatiotemporal synchronization. UAV launch, service, and recovery must align with truck arrivals at compatible locations and within feasible time windows. Small changes in truck routing

can invalidate otherwise feasible sorties. Synchronization constraints can therefore quickly dominate the feasible region [56]. This effect becomes stronger in tightly coordinated settings with multiple agents and frequent rendezvous interactions [7].

Energy feasibility is a second major challenge. UAV endurance depends not only on distance but also on payload, wind, and flight path geometry. Capturing these effects often requires nonlinear functions or scenario-based representations. This increases model size and can weaken linear relaxations. Beyond nominal energy estimation, models must also preserve feasibility under environmental variability, especially in dense networks with frequent short missions where limited slack makes recovery sensitive to disturbances [124].

Modeling complexity further escalates in multi-UAV and multi-tier configurations. Parallel sorties can create launch and recovery conflicts, handling bottlenecks at rendezvous locations, and coordination dependencies across UAVs. If these constraints are simplified or omitted, performance may be overestimated [17, 88]. Two echelon systems add another layer of coupling through facility location and capacity decisions, which link strategic and operational decisions and challenge standard MILP formulations [111]. Dynamic and on-demand settings amplify these difficulties because feasibility must be maintained over time as requests arrive and vehicle states evolve [82]. Uncertainty in travel time and environmental conditions compounds the problem. Robust and stochastic formulations can grow rapidly once synchronization is retained explicitly. Although uncertainty is widely recognized as a key challenge, general modeling templates that offer a consistent trade-off between realism, tractability, and comparability across studies remain limited [49]. In urban environments, airspace and geometry constraints, such as no-fly zones, altitude limits, and designated corridors, further complicate modeling. These constraints introduce spatial restrictions that are difficult to reconcile with classical routing abstractions [125].

5.2 Operational challenges

At the operational level, a primary challenge is execution variability and the need for real-time coordination. Even when plans are feasible offline, synchronization between trucks and UAVs can be fragile during execution. Small delays from congestion, signal control, or curb access constraints can propagate through tightly coupled schedules. This propagation can lead to missed rendezvous, increased waiting, or sortie cancellation. Empirical evidence indicates that launch and recovery timing must align with truck stopping patterns to preserve efficiency gains [56]. In multi-UAV operations, limited handling capacity at rendezvous locations can create local congestion and queuing. This motivates the use of flexible

launch and recovery locations, including non-customer sites, to relieve bottlenecks [16].

Energy management adds another set of operational constraints. Frequent sorties accelerate battery depletion and create requirements for charging, battery replacement, or reserve capacity. Reliability-oriented operations often add energy buffers to hedge against disturbances. Such buffers reduce effective utilization and can limit multi-sortie chaining, particularly during peak demand periods when schedule slack is scarce [60]. Weather exposure further affects operational stability. Wind, precipitation, and temperature can change flight time and energy use, which directly affects rendezvous feasibility and schedule robustness. These effects can be pronounced in dense urban environments where local airflow is complex, and constraints on airspace geometry reduce rerouting flexibility [125]. Survey evidence treats weather sensitivity as a recurring operational factor and associates it with the need for monitoring, updated feasibility checks, and adaptive control policies [49].

Operational performance is also shaped by fleet coordination and system integration. Heterogeneous UAV capabilities require dispatch rules that account for payload limits, endurance variation, and turnaround time. Coordination also depends on facility capacity, including handling and charging throughput, which can become a binding constraint in multi-vehicle settings [88, 126]. Compliance requirements can introduce route detours, additional checks, and monitoring tasks that affect timing and energy consumption [26]. Reliable execution further depends on communication stability and failure handling procedures, such as contingency landing and degraded navigation modes. These mechanisms are critical in practice but are often simplified or omitted in operational models [100].

5.3 Regulatory, safety, and integration challenges

Regulatory and safety constraints play a decisive role in shaping the feasible design space of cooperative delivery systems. Airspace rules vary across regions and typically impose no-fly zones, altitude limits, and corridor requirements. Regulatory fragmentation and compliance requirements are repeatedly identified as deployment barriers in logistics-oriented drone delivery systems [127]. Evidence also indicates that airspace regulations can reduce operational viability and increase energy demand, thereby tightening synchronization windows with ground vehicles [58].

Safety considerations further restrict operations in mixed air and ground environments. UAVs must avoid collisions with buildings, obstacles, and other aerial vehicles [128]. System integration requires safety and security mechanisms, including redundancy, integrity assurance, and certification-oriented processes [129,

130]. Integration with ground transport infrastructure introduces additional sensitivity to congestion and curb access constraints, because minor truck delays can propagate into recovery infeasibility when rendezvous windows are narrow and alternative recovery options are limited [99, 126].

System-level interoperability poses another challenge. Cooperative delivery relies on continuous communication among UAVs, trucks, and control platforms. Communication latency, packet loss, and sensor noise can degrade synchronization accuracy and coordination reliability, particularly in multi-UAV settings where coordination decisions are frequent [127]. Privacy and public acceptance further shape permissible flight paths and operating windows. Survey-based evidence indicates that perceived privacy and noise concerns, as well as perceived risks, can reduce acceptance of drone delivery services, indirectly constraining feasible deployment strategies [69, 131].

Regulatory and safety constraints affect cooperative delivery through two pathways. One pathway is geometric feasibility, which reshapes reachable sets and can tighten rendezvous windows. The other pathway is compliance and system assurance, which adds operational overhead and latency that can be non-negligible in tightly synchronized operations. Evidence is most comparable when studies report the restriction set, compliance requirements, and the resulting detour and energy impacts, rather than only average routing costs.

5.4 Environmental, social, and sustainability challenges

Environmental, social, and sustainability considerations are increasingly central to the evaluation of truck–UAV cooperative delivery systems, yet they remain less consistently modeled than routing efficiency or computational performance. In this area, the key issue is not simply whether UAV-assisted delivery is “greener,” but under what spatial, operational, and boundary assumptions environmental and social advantages remain valid. As a result, comparative interpretation requires much greater attention to system boundaries, energy modeling detail, and deployment constraints than is typically needed for routing-cost comparisons alone.

Existing evidence suggests that UAV-assisted delivery can reduce operational energy use or emissions under some conditions, particularly when aerial service shortens detours, bypasses congested ground travel, or serves lightweight demand over short distances. However, the same literature also shows that these benefits are highly conditional. Reported gains weaken, and may even reverse, when sortie frequency is high, routing constraints induce extra repositioning, or weather and energy uncertainty reduce operational slack [66]. Likewise, comparative results depend strongly on payload assumptions,

network density, and electricity mix [38]. This means that environmental gains reported in one study should not be interpreted as broadly transferable unless the underlying assumptions about customer distribution, energy source, and fleet operation are sufficiently aligned.

A second source of variation arises from flight realism and environmental constraints. Studies that incorporate payload-dependent energy consumption, no-fly zones, and wind effects show that constrained airspace and atmospheric disturbances can materially increase both energy use and performance variability [77, 132]. These findings are important because they indicate that environmental performance is not only a function of route length, but also of whether the modeled air operation remains feasible and efficient under realistic flight conditions. At the same time, many existing studies still rely on simplified three-dimensional or stylized flight representations, which suggests that current estimates may understate the variability and sensitivity of UAV energy consumption in real urban environments.

A third challenge concerns the boundary of sustainability assessment itself. A useful distinction is whether a study evaluates operational emissions only—that is, the energy use and emissions associated with delivery execution—or adopts a broader lifecycle boundary that also includes vehicle and battery production, degradation, replacement, recycling, and supporting infrastructure [67]. These two choices can lead to materially different conclusions. Operational comparisons may favor UAV-assisted delivery under short-distance and low-payload conditions, whereas lifecycle assessments can reduce or even overturn these advantages when battery replacement is frequent, the electricity mix is carbon intensive, or facility and charging operations are substantial [78, 111]. Thus, much of the apparent inconsistency in the sustainability literature reflects not a direct contradiction in empirical evidence, but differences in what is counted within the assessment boundary. Environmental assessments should therefore state whether conclusions are based on operational delivery impacts, supporting-system impacts, or lifecycle impacts, and should report sensitivity to electricity mix, battery lifetime, payload, sortie frequency, and facility utilization when these assumptions materially affect the results.

Social acceptance introduces an additional and often under-modeled sustainability dimension. Noise, visual intrusion, privacy concerns, and public perceptions of safety influence both regulatory restrictions and willingness to use drone-based services [69, 131]. Survey-based evidence consistently indicates that perceived noise and privacy risks reduce public acceptance. Yet these factors are rarely formalized as explicit objectives or constraints in truck–UAV routing models. Their main effect is often indirect: they shape allowable operating windows,

Table 8 Suggested reporting dimensions for comparable truck–drone cooperative delivery studies

Reporting dimension	Recommended information
Scenario and system configuration	Application context; fleet composition; number of trucks and UAVs; truck-launched, facility-supported, or multi-echelon structure; static or dynamic setting
Operational assumptions	UAV speed, payload, endurance, charging or battery replacement; launch and recovery rules; service times; time windows; no-fly zones or airspace restrictions
Synchronization and feasibility rules	Same-node return or moving rendezvous; waiting rules; parallel launches; energy-feasibility checks; contingency or repair mechanisms
Uncertainty and information setting	Demand, travel time, weather, accessibility; deterministic, stochastic, or robust representation; information revelation process and update frequency
Performance and sustainability metrics	Cost; completion time; profit; waiting or synchronization losses; service reliability; deadline violation; tail lateness; energy use or emissions
Benchmark and evaluation setting	Instance source; real-map or synthetic data; baseline methods; parameter settings; number of runs; sensitivity or out-of-sample tests where applicable
Reporting dimension	Recommended information
Scenario and system configuration	Application context; fleet composition; number of trucks and UAVs; truck-launched, facility-supported, or multi-echelon structure; static or dynamic setting
Operational assumptions	UAV speed, payload, endurance, charging or battery replacement; launch and recovery rules; service times; time windows; no-fly zones or airspace restrictions
Synchronization and feasibility rules	Same-node return or moving rendezvous; waiting rules; parallel launches; energy-feasibility checks; contingency or repair mechanisms
Uncertainty and information setting	Demand, travel time, weather, accessibility; deterministic, stochastic, or robust representation; information revelation process and update frequency

feasible flight corridors, landing or station locations, and the practical deployability of otherwise efficient routing plans. In this sense, social acceptance should not be viewed merely as an external implementation issue, but as a set of deployment constraints that can alter the feasible design space of cooperative delivery systems.

5.5 Reproducibility and comparability

Studies on truck–UAV cooperative delivery indicate that, although substantial progress has been made in modeling and algorithm design, cross-study comparability remains limited. Existing reviews have provided relatively systematic classifications in terms of problem variants, system configurations, modelling assumptions, and solution approaches, while also revealing the fragmented nature of the field: even when studies appear to address similar problems, they are often built on markedly different operational settings and analytical perspectives [41, 47–49]. As a result, reported improvements in cost, completion time, responsiveness, robustness, or sustainability are often difficult to compare directly across studies. A major source of this difficulty lies in differences in synchronization rules, fleet composition, energy models, launch-and-recovery settings, facility support, uncertainty representations, and application context.

This challenge is reflected not only in modelling scope but also in experimental design and evidence generation. Some problem classes still lack widely accepted benchmark sets, so researchers rely on modified classical instances or self-generated datasets. For example, Zhang et al. (2021) [72] generate test instances by modifying an existing benchmark for humanitarian network

assessment, while Peng et al. (2025) [80] explicitly note that standardized test datasets are still unavailable for dynamic emergency settings and therefore construct their own experimental instances following prior generation rules. Cui et al. (2024) [82] further combine Solomon-based benchmark instances with real operational data from Singapore and compare their method against multiple benchmark algorithms and coordination scenarios. Although this improves practical relevance, it also increases heterogeneity in experimental protocol. In uncertainty-aware settings, comparability becomes even more challenging because the evaluation framework itself depends on the available information. Deng et al. (2024) [87] show that stochastic optimization is more appropriate when sample data are sufficiently rich, whereas robust approaches are often better suited to limited-data settings. Taken together, these studies suggest that heterogeneity in truck–UAV cooperative delivery concerns not only what is modeled, but also how evidence is generated, validated, and interpreted.

Against this background, the field would benefit from a more consistent evaluation structure. To make this discussion more operational without imposing a single benchmark structure, Table 8 summarizes reporting dimensions that would improve comparability across heterogeneous truck–drone studies. These dimensions are intended to clarify the assumptions under which empirical results are obtained and to make reported improvements easier to interpret across different problem settings.

6 Future directions

6.1 Integrated system-level modelling frameworks

Future research should move toward unified modeling frameworks that jointly capture routing, energy management, facility location, and real time control decisions. Existing studies largely address these components in isolation, which limits their ability to represent continuous, city scale operations [26, 133]. Multi-layer models that integrate traffic states, demand dynamics, and weather inputs through shared state variables can improve realism. To remain operationally interpretable, such models should specify what information is available online, how frequently it is updated, and what decision latency is assumed. Comparability across methods improves when synchronization rules, feasibility checks, and performance metrics are reported consistently. For urban deployments, system-level models also need an explicit low-altitude airspace network layer, because corridor design and airspace capacity constraints can change reachable sets and tighten synchronization windows.

6.2 Scalable optimization architectures

Although exact methods for truck-drone routing have advanced significantly, their applicability remains limited to moderate problem sizes or simplified settings [54, 86]. Decomposition-based approaches and structured matheuristics can improve scalability, but challenges persist in large networks, heterogeneous fleets, and tightly synchronized operations [28, 63, 87]. Learning augmented optimization, where machine learning guides column selection, neighborhood search, or cut generation, is a promising direction for reducing computation time while preserving solution quality [57, 60]. To support reproducibility, studies should report computational budgets, termination criteria, and sensitivity to key assumptions alongside solution quality.

6.3 Learning-based and adaptive coordination

As cooperative delivery environments become more dynamic, learning-based and multi-agent approaches are increasingly studied for online coordination. This is most relevant when state updates are frequent and action spaces are large. Recent work demonstrates the potential of reinforcement learning to coordinate truck-UAV operations under time-varying demand and emergency conditions [45, 114]. However, transferability across networks, reliability under rare disruptions, and safety under partial observability remain key challenges. These challenges motivate hierarchical designs, constraint-aware learning, and systematic benchmarking against strong heuristic baselines under matched assumptions [41].

6.4 Uncertainty, resilience, and sustainability

Future work should further address uncertainty arising from demand variability, travel times, energy consumption, and extreme events. While stochastic and robust formulations have been proposed for truck-UAV routing [60, 83], limited understanding exists of how multiple uncertainty sources interact at the network scale once synchronization is modeled explicitly. Dynamic models addressing random requests and disaster response illustrate the potential of cooperative systems to support emergency logistics under infrastructure disruption [47, 99]. Progress would benefit from reporting reliability indicators and tail risk metrics, not only mean costs, especially for time-critical missions. Integrating resilience analysis with life cycle sustainability assessment is also necessary when conclusions rely on energy or emission benefits. Such benefits depend on system boundaries, electricity sources, and battery degradation [24, 67].

6.5 Regulation, airspace design, and benchmarking infrastructure

The interaction between UAV-vehicle systems and regulatory frameworks remains underexplored. Airspace restrictions, altitude rules, and zoning policies can substantially reshape feasible routing and service capacity. Future research could jointly design low-altitude corridors, hub networks, and truck routes under alternative policy scenarios [58]. Progress will be more cumulative when benchmarks, datasets, and evaluation protocols are shared. It also requires that studies disclose restriction sets, energy assumptions, and synchronization rules in reproducible form. Recent systematic reviews call for clearer reporting and stronger standardization to enable cumulative comparison across methods [47, 72, 99].

7 Conclusion

Research on UAV-vehicle cooperative delivery has progressed rapidly over the past decade, establishing a diverse methodological foundation and demonstrating measurable benefits for urban delivery operations and time critical logistics under specified synchronization rules, energy feasibility assumptions, and airspace constraints. Advances in synchronized routing, multi-echelon system design, uncertainty aware models, multi-UAV coordination, and dynamic decision making have clarified how aerial and ground cooperation can reduce detours and improve responsiveness when rendezvous feasibility is preserved and waiting penalties do not dominate the schedule. The field has also expanded from stylized instances toward larger networks and more diverse operational settings.

Despite these achievements, substantial gaps remain between algorithmic innovation and routine deployment. Current models still struggle to capture the

coupled effects of synchronization, airspace constraints, energy availability, and multi-agent interactions at operational scale. Existing optimization and learning-based approaches face scalability limitations in large urban networks, rich facility structures, and volatile on-demand environments. Operational barriers, including regulatory fragmentation, airspace capacity limitations, communication reliability, and public acceptance, continue to restrict widespread adoption. These gaps motivate evaluation practices that report boundary conditions, matched assumptions, and reliability metrics, rather than only average performance improvements.

Looking ahead, wider deployment will depend on the joint evolution of low-altitude airspace management, curb access operations, and reliable communication. Empirical claims will be most actionable when studies report boundary conditions, reliability metrics, and system-level sustainability assumptions in reproducible form. Approaches that combine fast state estimation with feasibility-preserving re-optimisation may improve responsiveness, but their value should be validated under realistic decision latency, communication loss, and stress test scenarios. Sustainability conclusions should also reflect explicit assessment boundaries, including facility operations and battery life cycle impacts.

Future research will be strengthened by cross-disciplinary evidence that links atmospheric variability, regulatory constraints, and operational data to comparable evaluation protocols across routing, optimization, and learning-based methods. As low-altitude corridor planning and UAV traffic management mature, UAV-vehicle cooperation may become a component of resilient and low-carbon logistics. Long-term success will depend on alignment between technological feasibility, regulatory implementability, and social acceptance constraints.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s12544-026-00808-2>.

Supplementary material 1

Author contributions

Y.L. conducted the literature review and drafted the manuscript; Y.F. contributed to analysis and manuscript revision; C.M. supervised the study and revised the manuscript. All authors reviewed and approved the final manuscript.

Funding

This research was supported by the National Natural Science Foundation of China (52502423, 72571121), the Ministry of Education of China Humanities and Social Sciences Youth Fund (25XJCZH011), the Gansu Provincial Science and Technology Plan – Basic Research Program Project (25JRRA221), the Industry Support Plan Project of the Department of Education of Gansu Province (2024CYZC-28), and the Tianyou Postdoctoral Science Foundation of Lanzhou Jiaotong University (LJTYBH-2026021).

Data availability

No datasets were generated or analysed during the current study.

Declarations

Competing interests

The authors declare no competing interests.

Received: 22 December 2025 / Accepted: 25 June 2026

Published online: 10 July 2026

References

1. Allen, J., Piecyk, M., & Piotrowska, M., et al. (2018). Understanding the impact of e-commerce on last-mile light goods vehicle activity in urban areas: The case of London. *Transportation Research Part D: Transport Environment Development and Sustainability*, 61, 325–338.
2. Pahwa, A., & Jaller, M. (2025). Assessing the sustainability of last-mile distribution strategies to manage expedited shipping with dynamic and stochastic demand. *Transportation Research Part E: Logistics and Transportation Review*, 201, 104273. <https://doi.org/10.1016/j.tre.2025.104273>.
3. 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. <https://doi.org/10.1002/net.21818>.
4. Goodchild, A., & Toy, J. (2018). Delivery by drone: An evaluation of unmanned aerial vehicle technology in reducing CO₂ emissions in the delivery service industry. *Transportation Research Part D: Transport and Environment*, 61, 58–67. <https://doi.org/10.1016/j.trd.2017.02.017>.
5. Thibbotuwawa, A., Bocewicz, G., Radzki, G., Nielsen, P., & Banaszak, Z. (2020). UAV mission planning resistant to weather uncertainty. *Sensors*, 20(2), 515. <https://doi.org/10.3390/s20020515>.
6. Li, X., Tupayachi, J., Sharmin, A., & Martinez Ferguson, M. (2023). Drone-aided delivery methods, challenge, and the future: A methodological review. *Drones*, 7(3), 191. <https://doi.org/10.3390/drones7030191>.
7. Gerrits, B., & Schuur, P. *Parcel delivery for smart cities: A synchronization approach for combined truck-drone-street robot deliveries*; proceedings of the 2021 Winter Simulation Conference (WSC), F, 2021 [C]. IEEE.
8. Wu, G., Mao, N., Luo, Q., Xu, B., Shi, J., & Suganthan, P. N. (2022). Collaborative truck-drone routing for contactless parcel delivery during the epidemic. *IEEE Transactions on Intelligent Transportation Systems*, 23(12), 25077–25091. <https://doi.org/10.1109/TITS.2022.3181282>.
9. Lyu, M., Liu, W., He, Q., & Wu, L. (2025). Urban food delivery service optimisation with coordinated delivery riders and drones. *Transportation Research Part E: Logistics and Transportation Review*, 204, 204. <https://doi.org/10.1016/j.tre.2025.104412>.
10. Li, Y., Liu, M., & Hu, H., et al. (2025). A cost analysis of the collaborative delivery mode of drones and riders in food delivery scenarios. *International Journal of Logistics Research Applications*, 1–30.
11. Kumbhani, C., Kant, R., & Shankar, R. (2026). Drone adoption for sustainable urban food delivery: Economic and environmental benefits. *Transportation Research Part D: Transport and Environment*, 150, 105086. <https://doi.org/10.1016/j.trd.2025.105086>.
12. Han, Y., Zhang, M., & Nan, P., et al. (2023). Two-stage heuristic algorithm for vehicle-drone collaborative delivery and pickup based on medical supplies resource allocation. *Journal of King Saud University - Computer and Information Sciences*, 35(10).
13. Chen, X., Wang, C., & Chen, H. Split-delivery-based collaborative delivery routing problem of trucks and drones in emergency rescue scenarios. In *Proceedings of the International Conference on Frontiers of Traffic and Transportation Engineering (FTTE 2024)*, F, 2025 [C]. SPIE.
14. Fu, T., Li, S., & Li, Z. (2025). Research on collaborative delivery Path planning for trucks and drones in parcel delivery. *Sensors*, 25(10), 3087. <https://doi.org/10.3390/s25103087>.
15. Zieher, S., Olcay, E., & Kefferpütz, K., et al. (2024). Drones for automated parcel delivery: Use case identification and derivation of technical requirements. *Transportation Research Interdisciplinary Perspectives*, 28, 101253. <https://doi.org/10.1016/j.trip.2024.101253>.
16. Han, B., Chi, T., & Sun, Z. (2025). Collaborative delivery problem of trucks and multiple drones: An en-route operation with flexible launch positions. *International Transactions in Operational Research*.

17. 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, 164. <https://doi.org/10.1016/j.tre.2022.102788>.
18. Bai, X., Ye, Y., Zhang, B., & Ge, S. S. (2023). Efficient Package delivery task assignment for truck and high capacity drone. *IEEE Transactions on Intelligent Transportation Systems*, 24(11), 13422–13435. <https://doi.org/10.1109/TITS.2023.3287163>.
19. Sun, W., Wu, L., & Zhang, F. An exact algorithm to solve vehicle routing problem with drones for delivery and surveillance tasks after disasters [J]. Available at SSRN 5077473, 2024.
20. Rave, A., & Fontaine, P. (2025). The location routing problem with time windows and load-dependent travel times for cargo bikes. *European Journal of Operational Research*, 323(1), 97–107. <https://doi.org/10.1016/j.ejor.2024.11.040>.
21. Rojas Vilorio, D., Solano-Charris E, L., Muñoz-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. <https://doi.org/10.1111/itor.12783>.
22. Sorbelli, F. B., Coro, F., Palazzetti, L., Pinotti, C. M., & Rigoni, G. (2023). How the wind can be leveraged for saving energy in a truck-drone delivery system. *IEEE Transactions on Intelligent Transportation Systems*, 24(4), 4038–4049. <https://doi.org/10.1109/TITS.2023.3234627>.
23. Liu, Y., Shi, J., Luo, Z., Hu, X., Pedrycz, W., & Liu, Z. (2024). Cooperated truck-drone routing with drone energy consumption and time windows. *IEEE Transactions on Intelligent Transportation Systems*, 25(12), 20390–20404. <https://doi.org/10.1109/TITS.2024.3478175>.
24. Cicek, D., Simsek, M., & Kantarci, B. (2025). Machine learning-driven truck-drone collaborative delivery for time- and energy-efficient last-mile deliveries. *Electronics*, 14(10), 2026. <https://doi.org/10.3390/electronics14102026>.
25. Bi, Z., Guo, X., & Wang, J., et al. (2024). Truck-drone delivery optimization based on multi-agent reinforcement learning. *Drones*, 8(1).
26. Chung, S. H., Sah, B., & Lee, J. (2020). Optimization for drone and drone-truck combined operations: A review of the state of the art and future directions. *Computers & Operations Research*, 123, 105004. <https://doi.org/10.1016/j.cor.2020.105004>.
27. Jeong, H. Y., & Song B, D. (2025). Optimization of urban logistics with multi-modal systems: A comprehensive study of the airship-vehicle routing problem. *Transportation Research Part E: Logistics and Transportation Review*, 204, 104415. <https://doi.org/10.1016/j.tre.2025.104415>.
28. Bektur, G. (2024). A reinforcement learning-based multiobjective heuristic algorithm for multiple-truck routing problems with heterogeneous drones. *Applied Soft Computing*, 167, 167. <https://doi.org/10.1016/j.asoc.2024.112290>.
29. 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, 104691. <https://doi.org/10.1016/j.trc.2024.104691>.
30. Arishi, A., & Ahuja, P. (2025). Multi-agent reinforcement learning for truck–drone routing in smart logistics: A comprehensive review. *Computers and Electrical Engineering*, 127, 110529. <https://doi.org/10.1016/j.compeleceng.2025.110529>.
31. Zhang, W., Wang, G., & Liu, Q. (2025). Collaborative optimization of truck-drone based on multi-agent reinforcement learning [C]. *Proceedings of the International Joint Conference on Rough Sets*, FJ. Springer.
32. , 2025, November 5). Amazon activates prime air drone delivery in waco two days after pontiac launch. Z. <https://droneixl.co/2025/11/05/amazon-prime-air-drone-delivery-waco-tx/>.
33. , 2025, November 17). Amazon's prime air drone delivery service officially launches in San Antonio. Z. <https://www.ksat.com/news/local/2025/11/17/amazons-prime-air-drone-delivery-service-officially-launches-in-san-antonio/>.
34. 2025, September 16). Country's low-altitude economy aims sky high [Z]. http://www.chinadaily.com.cn/a/202509/16/WS568c89f79a3108622abca0e79_4.htm.
35. 2025, April 23). Meituan secures China's first nationwide drone delivery license, ramping up competition with Google wing. Z. <https://technode.com/2025/04/23/meituan-secures-chinas-first-nationwide-drone-delivery-licens-e-ramping-up-competition-with-google-wing/>.
36. Dell'amico, M., Montemanni, R., & Novellani, S. (2020). Matheuristic algorithms for the parallel drone scheduling traveling salesman problem. *Annals of Operations Research*, 289(2), 211–226. <https://doi.org/10.1007/s10479-020-03562-3>.
37. Kitjacharoenchai, P., Ventresca, M., & Moshref-Javadi, M., et al. (2019). Multiple traveling salesman problem with drones: Mathematical model and heuristic approach. *Computers & Industrial Engineering*, 129, 14–30. <https://doi.org/10.1016/j.cie.2019.01.020>.
38. Chiang, W.-C., Li, Y., Shang, J., & Urban, T. L. (2019). Impact of drone delivery on sustainability and cost: Realizing the UAV potential through vehicle routing optimization. *Applied Energy*, 242, 1164–1175. <https://doi.org/10.1016/j.apenergy.2019.03.117>.
39. Li, Y., Liu, M., & Jiang, D. (2022). Application of unmanned aerial vehicles in logistics: A literature review. *Sustainability*, 14(21), 14473. <https://doi.org/10.3390/su142114473>.
40. Jazemi, R., Alidadiani, E., Ahn, K., & Jang, J. (2023). A review of literature on vehicle routing problems of last-mile delivery in urban areas. *Applied Sciences*, 13(24), 13015. <https://doi.org/10.3390/app132413015>.
41. Macrina, G., Di Puglia Pugliese, L., & Guerriero, F., et al. (2020). Drone-aided routing: A literature review. *Transportation Research Part C: Emerging Technologies*, 120.
42. Vilorio, D. R., Solano-Charris E, L., Muñoz-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. <https://doi.org/10.1111/itor.12783>.
43. Li, H., Chen, J., Wang, F., & Bai, M. (2021). Ground-vehicle and unmanned-aerial-vehicle routing problems from two-echelon scheme perspective: A review. *European Journal of Operational Research*, 294(3), 1078–1095. <https://doi.org/10.1016/j.ejor.2021.02.022>.
44. Moshref-Javadi, M., & Winkenbach, M. (2021). Applications and Research avenues for drone-based models in logistics: A classification and review. *Expert Systems with Applications*, 177, 177. <https://doi.org/10.1016/j.eswa.2021.114854>.
45. Dukkanci, O., Campbell J, F., & Kara B, Y. (2024). Facility location decisions for drone delivery: A literature review. *European Journal of Operational Research*, 316(2), 397–418. <https://doi.org/10.1016/j.ejor.2023.10.036>.
46. Dang, S., Liu, Y., & Luo, Z., et al. (2024). A survey of the routing problem for Cooperated trucks and drones. *Drones*, 8(10).
47. Duan, J., Luo, H., & Wang, G. (2025). Approaches to the truck-drone routing problem: A systematic review. *Swarm and Evolutionary Computation*, 92, 92. <https://doi.org/10.1016/j.swevo.2024.101825>.
48. Luo, H., Duan, J., & Wang, G. (2025). Mathematical models for truck-drone routing problem: Literature review. *Applied Mathematical Modelling*, 144, 144. <https://doi.org/10.1016/j.apm.2025.116074>.
49. Faramarzadeh, M., & Akpinar, S. (2025). A literature review of collaborative truck and drone in last-mile delivery. *Computers & Industrial Engineering*, 209, 209. <https://doi.org/10.1016/j.cie.2025.111477>.
50. Qi, B., & Li, G. (2024). The evolution of the cold chain logistics vehicle routing problem: A bibliometric and visualization review. *Digital Transportation Safety*, 3(3), 92–114.
51. Murray, C. C., & Chu A, G. (2015). The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery. *Transportation Research Part C: Emerging Technologies*, 54, 86–109. <https://doi.org/10.1016/j.trc.2015.03.005>.
52. Boysen, N., Briskorn, D., Fedtke, S., & Schwerdfeger, S. (2018). Drone delivery from trucks: Drone scheduling for given truck routes. *Networks*, 72(4), 506–527. <https://doi.org/10.1002/net.21847>.
53. Quang Minh, H., Deville, Y., & Quang Dung, P., et al. (2018). On the min-cost traveling salesman problem with drone. *Transportation Research Part C: Emerging Technologies*, 86, 597–621.
54. Roberti, R., & Ruthmair, M. (2021). Exact methods for the traveling salesman problem with drone. *Transportation Science*, 55(2), 315–335. <https://doi.org/10.1287/trsc.2020.1017>.
55. Cavani, S., Iori, M., & Roberti, R. (2021). Exact methods for the traveling salesman problem with multiple drones. *Transportation Research Part C: Emerging Technologies*, 130, 103280. <https://doi.org/10.1016/j.trc.2021.103280>.
56. De Freitas, J. C., & Vaz Penna P, H. (2020). A variable neighborhood search for flying sidekick traveling salesman problem. *International Transactions in Operational Research*, 27(1), 267–290. <https://doi.org/10.1111/itor.12671>.
57. Franco, J. L., Curtis, V. V., Senne E L, F., & Verri, F. A. N. (2025). An exact method and a heuristic for last-mile delivery drones routing with centralized graph-based airspace control. *Computers & Operations Research*, 178, 107006. <https://doi.org/10.1016/j.cor.2025.107006>.
58. Elsayed, M., & Mohamed, M. (2020). The impact of airspace regulations on unmanned aerial vehicles in last-mile operation. *Transportation Research Part*

- D: Transport and Environment*, 87, 102480. <https://doi.org/10.1016/j.trd.2020.102480>.
59. Alfandari, L., Ljubić, I., & De Melo da Silva, M. (2022). A tailored Benders decomposition approach for last-mile delivery with autonomous robots. *European Journal of Operational Research*, 299(2), 510–525. <https://doi.org/10.1016/j.ejor.2021.06.048>.
60. Wang, F., Li, H., & Xiong, H. (2025). Truck–drone routing problem with stochastic demand. *European Journal of Operational Research*, 322(3), 854–869. <https://doi.org/10.1016/j.ejor.2024.11.036>.
61. Wang, D., Hu, P., & Du, J., et al. (2019). Routing and scheduling for hybrid truck-drone collaborative parcel delivery with independent and truck-carried drones. *IEEE Internet of Things Journal*, 6(6), 10483–10495. <https://doi.org/10.1109/JIOT.2019.2939397>.
62. Agatz, N., Bouman, P., & Schmidt, M. (2018). Optimization approaches for the traveling salesman problem with drone. *Transportation Science*, 52(4), 965–981. <https://doi.org/10.1287/trsc.2017.0791>.
63. Barzanjeh, S., Ahmadizar, F., & Arkat, J. (2025). Logic-based benders decomposition algorithm for robust parallel drone scheduling problem considering uncertain travel times for drones. *Transportation Research Part E: Logistics and Transportation Review*, 193, 103877. <https://doi.org/10.1016/j.tre.2024.103877>.
64. Pei, Z., Liu, Y., Dai, X., Yuan, Y., & Liu, C. (2023). When drone delivery meets human courier: A co-sourcing perspective. *Transportation Research Part C: Emerging Technologies*, 156, 104333. <https://doi.org/10.1016/j.trc.2023.104333>.
65. Chen, H., Hu, Z., & Solak, S. (2021). Improved delivery policies for future drone-based delivery systems. *European Journal of Operational Research*, 294(3), 1181–1201. <https://doi.org/10.1016/j.ejor.2021.02.039>.
66. Kirschstein, T. (2020). Comparison of energy demands of drone-based and ground-based parcel delivery services. *Transportation Research Part D: Transport and Environment*, 78, 78. <https://doi.org/10.1016/j.trd.2019.102209>.
67. Bao, D., Yan, Y., Li, Y., & Chu, J. (2025). The future of last-mile delivery: Lifecycle environmental and economic impacts of drone-truck parallel systems. *Drones*, 9(1), 54. <https://doi.org/10.3390/drones9010054>.
68. Wang, Z., & Sheu, J.-B. (2019). Vehicle routing problem with drones. *Transportation Research Part B: Methodological*, 122, 350–364. <https://doi.org/10.1016/j.trb.2019.03.005>.
69. Mathew, A. O., Jha, A. N., Lingappa, A. K., & Sinha, P. (2021). Attitude towards drone food delivery services—role of innovativeness, perceived risk, and green image. *Journal of Open Innovation: Technology, Market, and Complexity*, 7(2), 144. <https://doi.org/10.3390/joitmc7020144>.
70. Gu, R., Poon, M., Luo, Z., Liu, Y., & Liu, Z. (2022). A hierarchical solution evaluation method and a hybrid algorithm for the vehicle routing problem with drones and multiple visits. *Transportation Research Part C: Emerging Technologies*, 141, 141. <https://doi.org/10.1016/j.trc.2022.103733>.
71. Rabta, B., Wankmüller, C., & Reiner, G. (2018). A drone fleet model for last-mile distribution in disaster relief operations. *International Journal of Disaster Risk Reduction*, 28, 107–112. <https://doi.org/10.1016/j.ijdrr.2018.02.020>.
72. Zhang, G., Zhu, N., Ma, S., & Xia, J. (2021). Humanitarian relief network assessment using collaborative truck-and-drone system. *Transportation Research Part E: Logistics and Transportation Review*, 152, 152. <https://doi.org/10.1016/j.tre.2021.102417>.
73. Delle Donne, D., Alfandari, L., & Archetti, C., et al. (2023). Freight-on-transit for urban last-mile deliveries: A strategic planning approach. *Transport Res B-Meth*, 169, 53–81.
74. De Maio, A., Ghiani, G., Laganà, D., & Manni, E. (2024). Sustainable last-mile distribution with autonomous delivery robots and public transportation. *Transportation Research Part C: Emerging Technologies*, 163, 104615. <https://doi.org/10.1016/j.trc.2024.104615>.
75. Osorio, J., & Ouyang, Y. (2025). To ride or to fly: Optimal freight-on-transit operations using drones. *Transportation Research Part E: Logistics and Transportation Review*, 201, 201. <https://doi.org/10.1016/j.tre.2025.104231>.
76. Stokkink, P., & Geroliminis, N. (2025). On the optimal micro-hub locations in a multi-modal last-mile delivery system. *Transportation Research Part E: Logistics and Transportation Review*, 203, 104344. <https://doi.org/10.1016/j.tre.2025.104344>.
77. Jeong, H. Y., Song, B. D., & Lee, S. (2019). Truck-drone hybrid delivery routing: Payload-energy dependency and no-fly zones. *International Journal of Production Economics*, 214, 220–233. <https://doi.org/10.1016/j.ijpe.2019.01.010>.
78. Rave, A., Fontaine, P., & Kuhn, H. (2023). Drone location and vehicle fleet planning with trucks and aerial drones. *European Journal of Operational Research*, 308(1), 113–130. <https://doi.org/10.1016/j.ejor.2022.10.015>.
79. Tirkolaee, E. B., Cakmak, E., & Karadayi-Usta, S. (2025). Traveling salesman problem with drone and bicycle: Multimodal last-mile e-mobility. *International Transactions in Operational Research*, 32(6), 3232–3258. <https://doi.org/10.1111/itor.13452>.
80. Peng, W., Wang, D., Yin, Y., & Cheng, T. C. E. (2025). Multi-agent deep reinforcement learning-based truck-drone collaborative routing with dynamic emergency response. *Transportation Research Part E: Logistics and Transportation Review*, 195, 103974. <https://doi.org/10.1016/j.tre.2025.103974>.
81. Vu, L., Vu, D. M., Hà, H., & Nguyen, V.-P. (2022). The two-echelon routing problem with truck and drones. *International Transactions in Operational Research*, 29(5), 2968–2994. <https://doi.org/10.1111/itor.13052>.
82. Cui, H., Li, K., Jia, S., & Meng, Q. (2024). Dynamic collaborative truck-drone delivery with en-route synchronization and random requests. *Transportation Research Part E: Logistics and Transportation Review*, 192, 103802. <https://doi.org/10.1016/j.tre.2024.103802>.
83. Yin, Y., Yang, Y., & Yu, Y., et al. (2023). Robust vehicle routing with drones under uncertain demands and truck travel times in humanitarian logistics. *Transport Res B-Meth*, 174, 174.
84. Liu, W., He, Y., & Ke G, Y., et al. (2025). On-demand meal delivery: Drone scheduling with battery replacement optimization. *Computers Operations Research Perspectives*, 107295.
85. 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, 151. <https://doi.org/10.1016/j.trc.2023.104139>.
86. Schmidt, J., Tilk, C., & Irnich, S. (2025). Exact solution of the vehicle routing problem with drones. *Transportation Science*, 59(1), 60–80. <https://doi.org/10.1287/trsc.2024.0544>.
87. Deng, M., Li, Y., Ding, J., Zhou, Y., & Zhang, L. (2024). Stochastic and robust truck-and-drone routing problems with deadlines: A benders decomposition approach. *Transportation Research Part E: Logistics and Transportation Review*, 190, 103709. <https://doi.org/10.1016/j.tre.2024.103709>.
88. Kitjacharoenchai, P., Min, B.-C., & Lee, S. (2020). Two echelon vehicle routing problem with drones in last mile delivery. *International Journal of Production Economics*, 225, 225. <https://doi.org/10.1016/j.ijpe.2019.107598>.
89. Montemanni, R., Dell'Amico, M., & Corsini, A. (2024). Parallel drone scheduling vehicle routing problems with collective drones. *Computers & Operations Research*, 163, 163. <https://doi.org/10.1016/j.cor.2023.106514>.
90. Delle Donne, D., Santini, A., & Archetti, C. (2025). Integrating public transport in sustainable last-mile delivery: Column generation approaches. *European Journal of Operational Research*, 324(1), 75–91.
91. 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. <https://doi.org/10.1016/j.trc.2019.11.003>.
92. Gao, J., Zhen, L., Laporte, G., & He, X. (2023). Scheduling trucks and drones for cooperative deliveries. *Transportation Research Part E: Logistics and Transportation Review*, 178, 178. <https://doi.org/10.1016/j.tre.2023.103267>.
93. Gao, J., Zhen, L., & Wang, S. (2023). Multi-trucks-and-drones cooperative pickup and delivery problem. *Transportation Research Part C: Emerging Technologies*, 157, 157. <https://doi.org/10.1016/j.trc.2023.104407>.
94. Bruni, M. E., Khodaparasti, S., & Perboli, G. (2023). The drone latency location routing problem under uncertainty. *Transportation Research Part C: Emerging Technologies*, 156, 104322. <https://doi.org/10.1016/j.trc.2023.104322>.
95. Figliozzi, M. A. (2020). Carbon emissions reductions in last mile and grocery deliveries utilizing air and ground autonomous vehicles. *Transportation Research Part D: Transport Environment Development and Sustainability*, 85, 102443. <https://doi.org/10.1016/j.trd.2020.102443>.
96. Zhang, R., Xiao, J., & Heinitz, F. (2025). Urban case studies on optimized truck-drone last-mile distribution. *Transportation Research Procedia*, 83, 19–27. <https://doi.org/10.1016/j.trpro.2025.02.005>.
97. Khalaj Rahimi, S., & Rahmani, D. (2025). A hybrid multi-objective solution approach for a reliable truck-drone routing problem integrated with pickup and delivery services. *Transportation Letters—the International Journal of Transportation Research*, 17(2), 230–248. <https://doi.org/10.1080/19427867.2024.2336339>.
98. Wang, Y., Wang, Z., & Hu, X., et al. (2022). Truck-drone hybrid routing problem with time-dependent road travel time. *Transportation Research Part C: Emerging Technologies*, 144, 144.
99. Li, K., Cui, H., Meng, Q., & Zhang, X. (2025). Dynamic truck-drone collaborative transportation during hurricanes. *Transportation Research Part C: Emerging Technologies*, 180, 180. <https://doi.org/10.1016/j.trc.2025.105322>.

100. She, R., & Ouyang, Y. (2024). Hybrid truck-drone delivery under aerial traffic congestion. *Transport Res B-Meth*, 185.
101. Tureci-Isik, H., Çelik, M., & Sanci, E. (2025). The stochastic location-routing problem with parallel truck-drone operations for humanitarian aid delivery. *European Journal of Operational Research*.
102. Colajanni, G., Daniele, P., & Nagurney, A. (2023). Centralized supply chain network optimization with UAV-based last mile deliveries. *Transportation Research Part C: Emerging Technologies*, 155, 155. <https://doi.org/10.1016/j.trc.2023.104316>.
103. Dukkanci, O. (2026). A truck–drone delivery problem with location and routing decisions under uncertainty. *Omega*, 139, 139. <https://doi.org/10.1016/j.omega.2025.103446>.
104. Liu, Y., Liu, Z., Shi, J., Wu, G., & Pedrycz, W. (2021). Two-echelon routing problem for parcel delivery by Cooperated truck and drone. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 51(12), 7450–7465. <https://doi.org/10.1109/TSMC.2020.2968839>.
105. Van Steenberghe, R., Mes, M., & Van Heeswijk, W. (2023). Reinforcement learning for humanitarian relief distribution with trucks and UAVs under travel time uncertainty. *Transportation Research Part C: Emerging Technologies*, 157, 104401. <https://doi.org/10.1016/j.trc.2023.104401>.
106. Paul, A., Levin, M. W., Waller, S. T., & Rey, D. (2025). Data-driven optimization for drone delivery service planning with online demand. *Transportation Research Part E: Logistics and Transportation Review*, 198, 104095. <https://doi.org/10.1016/j.tre.2025.104095>.
107. Qiu, H., Luo, Z., & Huang, Y., et al. (2025). Relational trajectory-entropy augmented MADRL for truck-drone collaborative deliver with mobile charging optimization. *IEEE Transactions on Intelligent Transportation Systems*, 1–15.
108. Torabi, P., & Hemmati, A. (2025). A synchronized vessel and autonomous vehicle model for environmental monitoring: Mixed integer linear programming model and adaptive matheuristic. *Computers & Operations Research*, 183, 107188. <https://doi.org/10.1016/j.cor.2025.107188>.
109. Bai, X., Li, B., & Li, J., et al. (2025). Efficient routing for multitruck multidrone Package delivery with precedence constraints. *IEEE Transactions on Robotics*, 41, 6514–6528. <https://doi.org/10.1109/TRO.2025.3629808>.
110. Dukkanci, O., Campbell, J. F., & Kara, B. Y. (2024). Facility location decisions for drone delivery with riding: A literature review. *Computers & Operations Research*, 167, 167. <https://doi.org/10.1016/j.cor.2024.106672>.
111. Vu, L., Vu, D. M., & Hà, M., et al. (2022). The two-echelon routing problem with truck and drones. *International Transactions in Operational Research*, 29(5), 2968–2994. <https://doi.org/10.1111/itor.13052>.
112. Gonzalez-R P, L., Sanchez-Wells, D., & Andrade-Pineda, J. L. (2024). A bi-criteria approach to the truck-multidrone routing problem. *Expert Systems with Applications*, 243. <https://doi.org/10.1016/j.eswa.2023.122809>.
113. Xiao, J., Li, Y., Cao, Z., & Xiao, J. (2024). Cooperative trucks and drones for rural last-mile delivery with steep roads. *Computers & Industrial Engineering*, 187, 187. <https://doi.org/10.1016/j.cie.2023.109849>.
114. Xiang, C., Mo, Y., Liu, W., Wu, Z., & Li, L. (2025). Path pool based transformer model in reinforcement framework for dynamic urban drone delivery problem. *Transportation Research Part C: Emerging Technologies*, 177, 105165. <https://doi.org/10.1016/j.trc.2025.105165>.
115. Carlsson, J. G., & Song, S. (2018). Coordinated logistics with a truck and a drone. *Management Science*, 64(9), 4052–4069. <https://doi.org/10.1287/mnsc.2017.2824>.
116. Poikonen, S., & Golden, B. (2020). The mothership and drone routing problem. *INFORMS Journal on Computing*, 32(2), 249–262. <https://doi.org/10.1287/joc.2018.0879>.
117. 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. <https://doi.org/10.1016/j.trb.2020.11.011>.
118. Blufstein, M., Lera-Romero, G., & Soullignac, F. J. (2024). Incremental state-space relaxations for the basic traveling salesman problem with a drone. *INFORMS Journal on Computing*, 36(4), 1064–1083. <https://doi.org/10.1287/jijo.c.2022.0390>.
119. Boutilier, J. J., & Chan, T. C. Y. (2022). Drone network design for cardiac arrest response. *M & som-Manufacturing & Service Operations Management*, 24(5), 2407–2424. <https://doi.org/10.1287/msom.2022.1092>.
120. Liu, W., & Sun, X. (2022). Energy-aware and delay-sensitive management of a drone delivery system. *M & som-Manufacturing & Service Operations Management*, 24(3), 1294–1310. <https://doi.org/10.1287/msom.2021.1056>.
121. Zhu, L., Wang, T., Ma, X., Yang, L., & Lou, X. (2025). Route optimization of green truck-drone collaborative delivery with multiple drops considering demand distribution. *International Journal of Sustainable Transportation*, 19(9), 854–862. <https://doi.org/10.1080/15568318.2025.2493138>.
122. Zhou, B., Zeng, W., & Yang, H. (2025). Multi-trip UAV-UGV delivery network design with release times. *Transportation Research Part C: Emerging Technologies*, 181, 181. <https://doi.org/10.1016/j.trc.2025.105389>.
123. Zhen, L., Gao, J., Wang, S., Laporte, G., & Yue, X. (2025). Optimizing an on-demand delivery mode based on trucks and drones. *Transportation Science*, 59(5), 1008–1031. <https://doi.org/10.1287/trsc.2024.0693>.
124. Zhu, Y., Liu, M., & Jin, D. A short review of truck and drone collaborative delivery problem. In *Proceedings of the 2023 IEEE 10th International Conference on Cyber Security and Cloud Computing (CSCloud)/2023 IEEE 9th International Conference on Edge Computing and Scalable Cloud (EdgeCom)*, F, 2023 [C]. IEEE.
125. She, R., & Ouyang, Y. (2023). Analysis of drone-based last-mile delivery systems under aerial congestion: A continuum Approximation approach [R]: University of Michigan. Center for Connected and Automated Transportation.
126. Wang, Y., Yang, S., & Wang, X. V., et al. (2024). Research on truck-drone collaborative route planning for rural logistics delivery services. *Scientific Reports*, 14(1). <https://doi.org/10.1038/s41598-024-83149-1>.
127. Madani, B., & Ndiaye, M. Drone delivery systems for logistics operations: Identification of regulatory challenges. In *Proceedings of the 2023 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, F, 2023 [C]. IEEE.
128. Zhou, F., Shi, X., Bao, J., et al. (2025). Vehicle-aircraft conflict detection on the airport surface: An improved velocity obstacle method., 4(4), 251–263. <https://doi.org/10.48130/dts-0025-0024>.
129. Ajakwe, S. O., & Kim, D. S. (2024). Facets of security and safety problems and paradigms for smart aerial mobility and intelligent logistics. *IET Intelligent Transport Systems*, 18(S1), 2827–2855. <https://doi.org/10.1049/itr.2.12579>.
130. Wanner, D., Hashim, H. A., Srivastava, S., & Steinhauer, A. (2024). UAV avionics safety, certification, accidents, redundancy, integrity, and reliability: A comprehensive review and future trends. *Drone Systems and Applications*, 12, 1–23. <https://doi.org/10.1139/dsa-2023-0091>.
131. Dabić, M., Ferreira, J. J., & Lopes, J. M., et al. (2024). Consumer preferences and barriers in the adoption of drone delivery services: A comprehensive analysis. In *IEEE transactions on engineering management*.
132. Cheng, C., Adulyasak, Y., & Rousseau, L.-M. (2024). Robust drone delivery with weather information. *M & som-Manufacturing & Service Operations Management*, 26(4), 1402–1421. <https://doi.org/10.1287/msom.2022.0339>.
133. Moshref-Javadi, M., Hemmati, A., & Winkenbach, M. (2021). A comparative analysis of synchronized truck-and-drone delivery models. *Computers & Industrial Engineering*, 162, 162. <https://doi.org/10.1016/j.cie.2021.107648>.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.