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Review

Vehicle routing problem with trucks and drones collaboration: a structured literature review

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Abstract: Coordinated truck-drone delivery has emerged as an important extension of the vehicle routing problem (VRP), offering new opportunities to improve logistics efficiency, accessibility, and sustainability. In this review, we synthesize the literature on truck-drone routing by examining three interrelated themes: Vehicle routing and synchronization models, stochastic and dynamic operational constraints, and payload-energy management. Early studies primarily formulate truck-drone delivery as variants of heterogeneous or two-echelon VRP using mixed-integer linear programming (MILP) to capture coupled routing decisions, drone endurance limits, and launch-retrieval feasibility, often supplemented by heuristic or metaheuristic strategies to address computational scalability. More recent research extends these formulations to stochastic and dynamic VRP settings by incorporating uncertain customer availability, time windows, vehicle delays, and weather disruptions, reflecting a shift toward adaptive routing under incomplete information. Parallel work on payload configuration and energy management investigates modular loading and battery-swapping mechanisms, demonstrating how load heterogeneity and energy constraints fundamentally reshape feasible routing structures. Extensions to multimodal VRP variants, including electric vehicle-drone systems and van-robot hybrids, further broaden applicability in dense and constrained urban environments. Despite these advances, most models remain grounded in static or weakly stochastic assumptions, with limited support for real-time updates or predictive decision-making. In this review, we identified the integration of data-driven prediction and learning-based optimization within dynamic VRP frameworks as a critical direction for advancing truck-drone delivery toward large-scale operational deployment.

Keywords: stochastic; vehicle routing problem (VRP); urban delivery; machine learning

1. Introduction

The vehicle routing problem (VRP) has long served as a foundational model for optimizing freight transport and distribution systems. As logistics networks become more complex, numerous variants of the VRP have been proposed to reflect real-world delivery structures and constraints. Among these, the integration of heterogeneous fleets and multi-echelon delivery systems has been particularly influential in urban contexts, where large trucks often deliver to intermediate facilities or satellites, and smaller vehicles such as drones, vans, or cargo bikes handle the last-mile distribution [1]. With the emergence of lightweight and low cost aerial platforms, particularly unmanned aerial vehicles (UAVs) or drones, the VRP has been extended to include truck and drone collaboration. These truck-drone VRPs explore how drones can complement ground vehicles by leveraging their speed, flexibility, and ability to bypass traffic congestion.

Hybrid systems that combine independent drones with truck-carried drones have been explored to leverage the complementary strengths of trucks (capacity, range) and drones (speed, accessibility) [2]. Subsequent work formalized this multi-vehicle interaction more rigorously through the definition of the two-echelon VRP with drones (2EVRPD), where multiple trucks function as mobile depots and drones are permitted to perform several deliveries per sortie before returning [3]. This formalization represents the first explicit problem statement for the 2EVRPD and has become a foundational reference point for studies on truck-drone coordination.

Applications of VRP with trucks and drones generally fall into two broad categories: Urban delivery and emergency logistics. In urban contexts, researchers have primarily addressed the challenges of traffic congestion, limited road access, and regulatory restrictions. For example, large trucks are often inefficient or prohibited in narrow inner-city streets, while European low-emission and zero-emission zones further encourage the use of electric vans, cargo bikes, or drones for last-mile distribution [4]. In contrast, emergency logistics emphasizes flexibility and resilience, as drones enable access to otherwise unreachable locations such as rural households, mountainous areas, or disaster zones [5].

The integration of drones into VRP frameworks offers several distinct benefits. First, drones can bypass traffic restrictions, flying directly between origin and destination without being constrained by road conditions [2]. Second, they extend accessibility to remote or isolated areas that ground vehicles cannot reach [5]. Third, they enhance delivery speed, providing faster service for time-critical items [6]. Finally, drones enhance resilience in emergencies, maintaining service continuity during hurricanes, floods, or pandemics when conventional transport is disrupted [5].

The remainder of this paper is organized as follows: In Section 2, we analyze the major application scenarios of VRP with trucks and drones. In Section 3, we review key research contributions addressing truck-drone synchronization. In Section 4, we examine the operational limitations of drones, including endurance and payload capacity. In Section 5, we discuss the integration of novel vehicle types into parcel-delivery systems. Finally, in Section 6, we summarize the research methods observed across different scenarios and conclude with future research directions.

2. Applications of VRP with trucks and drones

As discussed, VRP plays a central role in optimizing logistics and improving the efficiency of transportation systems. With the rapid advancement of technologies such as electric vehicles, autonomous drones, and real-time data analytics, VRP applications have expanded into increasingly dynamic and specialized delivery contexts. In particular, emerging scenarios involving electric truck delivery, drone-based last-mile distribution, and truck-drone collaborative systems have introduced new challenges and opportunities, prompting the development of tailored VRP solutions for modern logistics networks.

Early efforts to integrate drones into logistics were motivated by the challenge of remote deliveries. The hybrid truck-drone delivery (HTDD) system combines trucks, truck-carried drones, and independent drones in a three-layer framework. While the design promised high efficiency for sparsely distributed customers, it also highlighted the routing complexity of coordinating multiple delivery platforms [7], as illustrated in Figure 1.

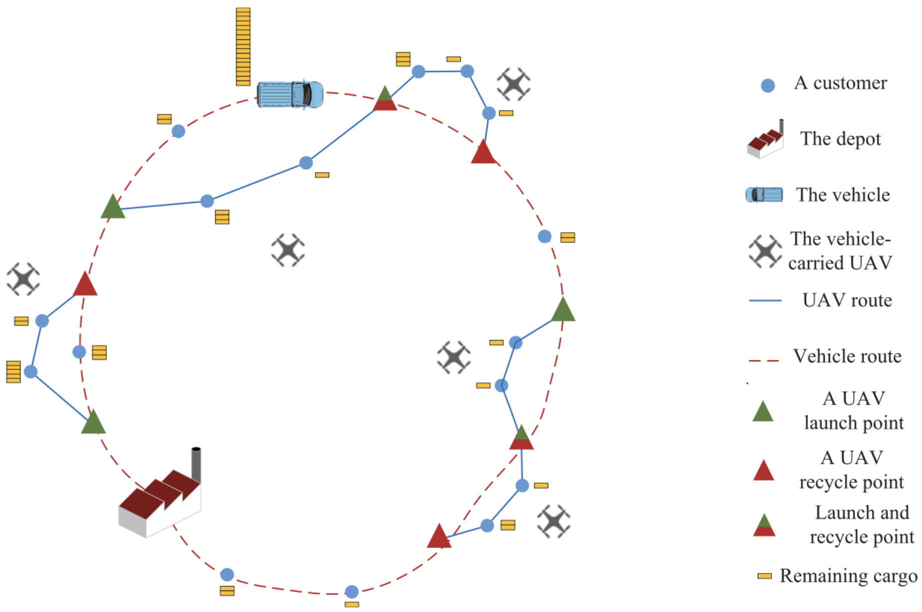

Figure 1. Hybrid truck-drone delivery (HTDD).

The accompanying HTDD formalizes this challenge mathematically for large-scale implementation, underscoring the system's potential to transform current delivery practices.

Building on the theme of hybridization, Wang et al. [2] introduced the VRP with drones (VRPD), extending the classical capacitated VRP by enabling drones to travel with trucks, serve customers, and rendezvous at service hubs. Their mixed-integer programming formulation with a branch-and-price algorithm achieved 20% cost reductions and shorter delivery times compared to truck-only routing. Unlike the remote-oriented HTDD, VRPD emphasized hub coordination and pointed to the importance of improved drone battery technologies for further cost savings.

This line of research has since expanded toward multi-drone coordination. Leon-Blanco et al. [8] addressed the truck-multi-drone team logistics problem (TmDTL) in which multiple UAVs assist a truck along a delivery route. Using an agent-based modeling approach, they demonstrated scalability to very large instances with up to 500 customers and eight drones, showing that distributed decision-making can mitigate the local minima often encountered by centralized optimization methods. This perspective complements the VRPD framework of Wang et al. [2] by shifting the emphasis from cost and travel-time efficiency toward scalability and robustness in multi-drone operational settings.

Other researchers prioritized minimizing customer waiting times. Moshref-Javadi et al. [9] proposed the multi-trip traveling repairman problem with drones (MTRPD), where trucks repeatedly launch drones from stops. Their hybrid Simulated Annealing (SA)-Tabu Search algorithm significantly reduced waiting times, with key drivers being depot location, UAV-to-truck speed ratio, and reuse of UAVs. Similarly addressing synchronization but from another angle, Gonzalez et al. [10] introduced the truck-drone team logistics (TDTL) model, removing the assumption of fixed rendezvous points by letting drones recharge flexibly at dynamically chosen truck stops. Their iterated greedy plus SA heuristic proved scalable across more than 1,000 benchmarks, suggesting readiness for real-world deployment. Both entailed extending the VRPD and TmDTL lines by focusing on operational constraints like rendezvous flexibility and time-sensitive service.

Beyond these, Karak et al. [11] explored the hybrid vehicle-drone routing problem (HVDRP), emphasizing pickup and delivery integration. Their hybrid clarke-wright heuristic showed that simultaneously optimizing vehicle and drone routing yields superior cost savings compared to sequential planning. Later works built on this integrated perspective by incorporating sustainability concerns. For instance, Kyriakakis et al. [12] and Mara et al. [13] extended HVDRP into electric vehicle (EV)-drone hybrids, examining charging infrastructure and power-sharing between vehicles and drones. Moreover, Morim et al. [6] introduced robot depots as intermediate stops, showing further potential for operational cost reduction. These directions represent the evolution from early three-layer systems (HTDD) toward modern, multi-modal frameworks that combine drones, trucks, EVs, and new infrastructure concepts.

Finally, Sluijk et al. [14] highlighted another frontier by incorporating stochastic demand into a 2EVRP. Their chance-constrained formulation ensures that second-echelon routes remain feasible with high probability, and their column-generation algorithms efficiently handle correlated or data-driven demand distributions. This complements deterministic truck-drone research by embedding uncertainty directly into the model, showing how hybrid logistics systems must not only optimize routes and infrastructure but also remain robust to demand fluctuations.

3. Synchronization of trucks and drones

A central challenge in urban truck-drone delivery systems is the synchronization of heterogeneous vehicles, particularly ensuring that drones can be launched, retrieved, and resupplied in coordination with truck routes. Several seminal researchers have approached this problem from different perspectives.

Kitjacharoenchai et al. [3] explicitly modeled truck-drone synchronization where multiple drones were deployed from a single truck. They proposed a decomposition-based truck and drone routing clustering (DTRC) approach combined with large neighborhood search (LNS) to minimize total delivery time. While effective, their model assumes only truck-carried drones, overlooking the potential of independent drones or additional modalities. This limitation is partially addressed in Wang et al. [7] who proposed a HTDD system in which truck-carried and independent drones must be jointly scheduled. In their formulation, the truck acts as a mobile depot for a set of carried drones, while independent drones operate directly from the depot to serve customers in parallel. The scheduling algorithm coordinates three platforms (truck, truck-carried drones, and independent drones) to exploit their complementary advantages: The truck provides capacity and mobility, truck-carried drones extend coverage around the truck's route, and independent drones enable direct long-range sorties without waiting for truck synchronization. By considering both drone types simultaneously, Wang et al. [7] explicitly modeled interdependence between fleets, demonstrating significant cost savings compared to systems limited to truck-carried drones only.

Similar to Kitjacharoenchai et al. [3], Moshref-Javadi et al. [9] developed a mixed-integer programming formulation to synchronise drone launches and returns along truck routes, with the goal of reducing customer waiting times. Their truck and drone routing algorithm (TDRA) demonstrated strong performance for realistic e-commerce cases. However, the researchers considered homogeneous fleets and did not extend to multiple drones or heterogeneous vehicle types. Researchers such as Leon-Blanco et al. [8] studied multi-drone fleets through an agent-based approach, highlighting the scalability of coordination when several drones operate concurrently, thereby complementing the earlier single-drone synchronization frameworks.

Wang et al. [2] introduced the VRP with drones (VRPD), where drones could rendezvous with multiple trucks at service hubs. Their branch-and-price solution captured endurance and payload constraints explicitly, making it a more realistic model for urban logistics. Yet, this formulation excluded independent drones and did not consider additional ground modalities. In contrast, Morim et al. [6] extended synchronization to a tri-modal setting, introducing robot stations alongside truck-drone tandems. Their general variable neighborhood search (GVNS) demonstrated that integrating robots reduces parcel capacity bottlenecks and improves coverage, although at the cost of added operational complexity. While synchronization has been addressed in increasingly sophisticated ways from single truck-drone pairings to multi-drone, multi-truck, and robot-augmented systems, no single study fully integrates all dimensions of coordination. This reveals a research opportunity for unified models that can simultaneously accommodate multi-drone fleets, endurance and payload constraints, and multimodal collaborations in realistic urban settings. As shown in Figure 2, these studies collectively illustrate the evolution of synchronization strategies, from early truck-carried drone models to complex multi-modal systems, highlighting progress and remaining gaps in the literature.

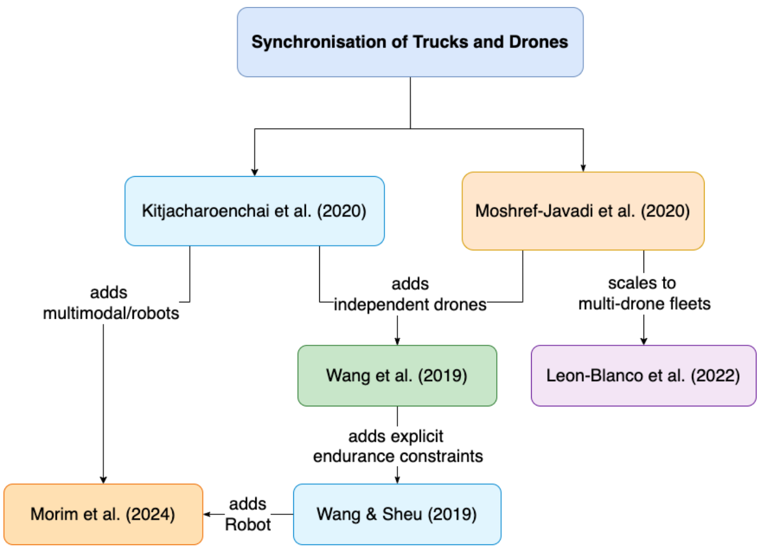

Figure 2. Truck and drone synchronization.

4. Limited drone endurance and capacity

The short battery life and low payload of drones remain the most cited barriers to scaling hybrid truck-drone systems in urban delivery. Early research sought to mitigate this by tightly coupling drones with truck routes. For instance, Kitjacharoenchai et al. [3] embedded drones into truck tours using decomposition-based clustering and large neighborhood search. By launching drones from the truck and requiring them to return before the truck moves on, the effective operating radius of drones was extended. This approach works because the truck acts as a mobile depot, enabling drones to cover short hops around the truck's path rather than attempting long-haul flights. Yet, such a design restricts flexibility, since only truck-drone tandems are considered. Researchers later addressed this rigidity: Wang et al. [7] added independent drones, enabling long-range sorties alongside truck-carried drones, while Kyriakakis et al. [12] and Mara et al. [13] integrated EVs into the system, directly modeling how payload weight and charging infrastructure influence endurance. These extensions show that endurance limits can be tackled not only by constraining drones within truck tours, but also by introducing additional fleet heterogeneity (independent drones, EVs) that absorb demands drones cannot meet alone.

Another stream of work approached endurance constraints by directly encoding them in optimisation formulations. Wang et al. [2] accounted for drone range and payload in a VRPD solved by branch-and-price, producing cost-efficient delivery plans under strict flight limits. However, because this remained a single-echelon system, opportunities for cross-modal synergy were under exploited. This gap was later bridged by Morim et al. [6], who added robot stations as a third modality, and Anderluh et al. [4], who showed that considering emissions, noise, and congestion as additional objectives changes how endurance trade-offs should be balanced. These complementary contributions highlight that endurance is not just a technical constraint but part of a broader system design problem: Extending reach may require adding new vehicle types or considering social and environmental objectives that make endurance constraints more binding in practice.

Heuristic and metaheuristic approaches have also emphasized endurance feasibility. Euchi et al. [15] combined mixed integer linear programming (MILP) with a hybrid genetic-sweep algorithm to ensure drones remained within their endurance limits while minimizing cost. Yet, this solution prioritized feasibility and efficiency under static assumptions. Complementary work has shown why static modeling is insufficient: Kyriakakis et al. [12] explicitly modeled how payload weight affects energy consumption, and Lichau et al. [5] incorporated hurricane conditions, where endurance decreases dynamically with wind intensity. These studies demonstrate that treating endurance as a fixed constraint underestimates its variability; instead, it is influenced by context such as payload weight or environmental disruptions, requiring adaptive modeling.

Capacity constraints have likewise shaped the problem model. Moshref-Javadi et al. [9] designed drones as single-parcel couriers, leaving bulk deliveries to the truck. This assumption reflects operational realism but sacrifices efficiency. Karak et al. [11] extended this by allowing multi-customer sorties, and Mara et al. [13] incorporated charging stations to coordinate EVs and drones under endurance limits. These extensions show that endurance and capacity challenges can be eased when infrastructure is introduced (charging/robot stations) or when operational rules are relaxed (multi-customer sorties). Importantly, new AI-driven methods offer further flexibility: Zhou et al. [16] introduced large language model (LLM)-enhanced Q-learning for multi-drone scheduling. These methods complement classical optimization by learning adaptive policies, offering a way to exploit fleeting opportunities that static endurance or capacity models cannot capture.

In summary, these studies show that endurance and payload limits are rarely solved by one mechanism alone. Embedding drones in truck tours extends range but limits flexibility; adding independent drones or EVs increases heterogeneity but raises coordination costs; and installing charging or robot stations expands effective endurance but adds complexity. Complementary methods from exact optimization to reinforcement-learning reveal that endurance is best managed when fleet design, infrastructure support, and adaptive scheduling are jointly considered. Relationships among these studies are summarized in Figure 3, illustrating how different approaches address endurance and capacity from multiple angles.

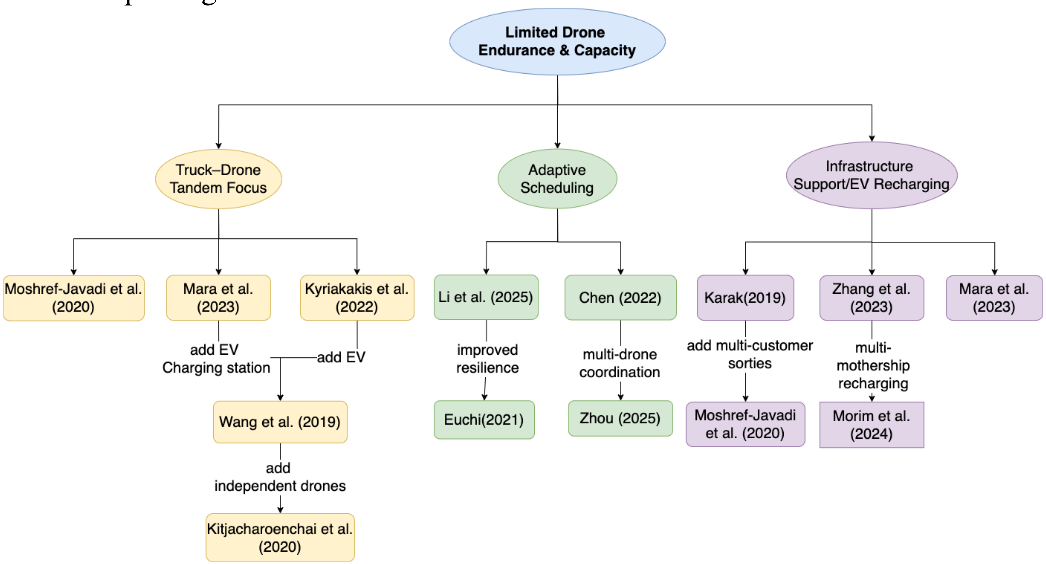

Figure 3. Limited drone capability.

5. Integration of novel vehicle types

The integration of novel vehicle types in logistics has evolved from isolated truck-drone pairings toward multi-echelon systems where EVs, UAVs, and ground robots interact under shared energy, spatial, and temporal constraints. This evolution is not driven by the introduction of new modes alone, but by attempts to overcome the structural limitations exposed in earlier models; energy feasibility, limited accessibility, synchronization complexity, and the inability to handle time-dependent operations.

A first wave of research framed integration primarily as an energy-endurance problem, particularly through EV-drone coordination [12]. These researchers used MILP-based formulations to explore the synergies between EV battery reserves and drone sortie feasibility, but they remained tied to road-network assumptions and static charging logic. Subsequent extensions introduced charging-station scheduling [13], addressing energy feasibility more realistically. However, both studies revealed a structural gap: Even well-energized motherships cannot solve spatial inaccessibility in dense urban or pedestrian-restricted regions.

This gap motivated a second trajectory in which vehicle integration becomes a spatial accessibility problem. Van-robot systems [1] illustrated how terrestrial robots extend reach into non-road zones where trucks and drones face restrictions on safety or airspace use. This represented an explicit response to the accessibility limitations of EV-drone systems: When endurance is no longer the bottleneck, the next constraint is domain of operation. Yet, in doing so, robot-based approaches introduced new synchronization challenges (handoff points, station availability, and work-zone partitioning), which EV-drone formulations largely abstracted away.

A third strand emerged when researchers attempted to combine endurance and accessibility into unified logistics architectures. Truck-drone-robot combinations [6] embody this shift: Drones offer rapid coverage, robots offer fine-grained access, and trucks provide high-capacity mobility. Their modeling approach, MILP for assignment plus heuristics for routing, reflects a methodological adaptation to the increased coordination complexity. These systems explicitly bridge the limitations observed in earlier EV-drone work (limited reach) and robot-based delivery (limited speed and range), but they treat operations as static, with fixed release times, known demand, and predetermined station locations.

The most recent progression reverses the traditional hierarchy of hybrid systems and recasts integration as a temporal throughput problem. By using UAVs as first-echelon carriers and UGV robots for the last mile, the UAV-UGV multi-trip architecture, Zhou et al. [17] synthesized the endurance-aware perspective of EV-drone studies [12, 13] with the accessibility-oriented logic of robot-assisted delivery [1, 6]. Importantly, it extended the modeling paradigm by incorporating multi-trip schedules and package release times, directly addressing the static-time assumption that constrained previous multimodal systems. Through this connection, Zhou et al. [17]'s formulation not only generalized earlier work but also exposed the next bottleneck: The absence of mechanisms to handle stochastic or real-time demand conditions.

Across these connected developments, as summarized in Table 1, the common limitation is determinism: Demand does not arrive in real time, travel times do not fluctuate, and inter-vehicle coordination is not adaptive. As the field progresses, integrating novel vehicle types requires not only combining new modes but restructuring multimodal logistics into uncertainty-aware, dynamically coordinated ecosystems, where the synergy between heterogeneous vehicles is governed by adaptive, data-driven intelligence rather than static synchronization rules.

Table 1. Integration of novel vehicable types.

	Vehicle	Key differentiator	Relation to earlier works
Kyriakakis (2022)	EV + Drone	Energy-efficient EV mothership; ignores recharging infrastructure	Establishes energy foundation
Mara (2023)	EV + Drone + Charging	Adds charging stations and endurance scheduling	Extends infrastructure realism
Yu (2022)	Van Robot	Ground robots for pedestrianised areas	Focuses on access and safety constraints
Morim (2024)	Truck + Drone + Robot Stations	Multimodal ground-aerial-robot cooperation	Explores spatial complementarity
Zhou (2025)	Drone + UGV	Reverses hierarchy: airborne main carrier + autonomous ground finisher; introduces multi-trip coordination and package release times	Expands the temporal-structural integration of vehicle types

6. Summary and conclusions

We reviewed three dominant research directions within truck-drone coordinated delivery systems. The first and most established direction concerns route planning, where authors construct formal mathematical models to encode system constraints and vehicle interactions. MILP remained the predominant framework [6, 11, 13], providing a basis upon which exact or heuristic methods generate initial feasible solutions that are subsequently refined using metaheuristics. Alternative formulations, such as Markov chains for modeling stochastic state transitions [18], illustrate an emerging interest in capturing dynamic behavior more rigorously.

The second direction focuses on time-window constraints and truck-drone operational conditions, which introduce uncertainty into service feasibility and route stability. For instance, Jeong et al. [19] assumed customers be available only for a fixed time window. Thus when the time window was missed, the delivery task was skipped automatically, whereas Teimoury et al. [18] assumed probabilistic customer availability, generating random delivery failures that necessitated adaptive rescheduling. These works highlighted the fragility of static routing plans and emphasize the need for dynamically responsive optimization, especially when disruptions arise from vehicle delays, environmental factors, or incomplete information.

The third direction is drone's payload management, driven by the operational limitations of drones with respect to endurance and carrying capacity. Studies in this stream explore how payload configuration affects routing feasibility, service coverage, and drone energy expenditure. Kyriakakis et al. [12] examined equal-sized but variably weighted payload modules, while Masmoudi et al. [20] conceptualized drone batteries as swappable payload elements handled on the truck in the same manner as parcels. These insights underscored the strong coupling between payload decisions, energy constraints, and synchronization requirements across heterogeneous vehicles.

It is important to recognize that these research directions are interdependent rather than mutually exclusive. Many researchers combine multiple themes, for example, embedding payload logic within stochastic routing models or integrating uncertainty handling within MILP formulations to construct a more realistic representation of truck-drone operation. However, most researchers assume static information, deterministic travel times, and limited forms of uncertainty. Few researchers address real-time node arrivals, dynamically changing customer states, or learning-based prediction of profitable delivery opportunities, which may be opportunities for future research on truck and drone collaborate delivery.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

Jun Shen is an editorial board member for Applied Computing and Intelligence and was not involved in the editorial review and the decision to publish this article.

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