

Article

Sustainable and Safe Last-Mile Delivery: A Multi-Objective Truck–Drone Matheuristic

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Abstract

Background: The rapid growth of e-commerce has intensified the need for last-mile delivery systems that can navigate urban congestion while minimizing environmental impact. Hybrid truck–drone networks offer a promising solution by combining heavy-duty ground transport with aerial flexibility; however, their deployment faces significant challenges in jointly managing operational risks, energy limits, and regulatory compliance. **Methods:** This study proposes a hybrid matheuristic framework to solve this multi-objective problem, simultaneously minimizing transportation cost, service time, energy consumption, and operational risk. A two-phase approach combines a metaheuristic for initial truck routing with a Mixed-Integer Linear Programming (MILP) formulation for optimal drone assignment and scheduling. This decomposition strikes a balance between exact optimization and computational scalability. **Results:** Experiments across various instance sizes (up to 100 customers) and fleet configurations demonstrate that integrating MILP enhances solution diversity and convergence compared to standalone strategies. Sensitivity analyses reveal significant impacts of drone speed and endurance on system efficiency. **Conclusions:** The proposed framework provides a practical decision-support tool for balancing complex trade-offs in time-sensitive, risk-constrained delivery environments, thereby contributing to more informed urban logistics planning.

Keywords: last-mile delivery; vehicle routing problem; truck–drone collaboration; multi-objective optimization; operational risk assessment; green logistics



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1. Introduction

The rapid expansion of e-commerce and rising customer expectations for expedited delivery have intensified the search for innovative solutions in last-mile logistics [1]. Among these, hybrid delivery systems integrating traditional trucks with Unmanned Aerial Vehicles (UAVs) have emerged as a promising alternative to conventional ground-based networks [2]. These systems leverage the complementary strengths of both platforms: UAVs provide flexible, rapid access to geographically dispersed or congested locations, while trucks facilitate high-capacity, long-distance transportation. This truck–drone synergy is particularly beneficial in urban and suburban environments [3], where reducing traffic congestion, carbon emissions, and service delays is critical [4]. This sustainability motivation is also supported by lifecycle-based analyses. For example, ref. [1] evaluates the environmental and economic implications of truck–drone parallel delivery systems

and shows that the magnitude of such benefits depends on operating conditions and scenario assumptions.

Beyond urban settings, recent studies have also demonstrated the efficacy of truck–drone delivery systems in rural and infrastructure-limited regions, where longer travel distances and sparse demand patterns reshape coordination requirements [5]. For example, refs [6,7] report improved service capability in challenging terrains, while also noting that environmental factors such as temperature can significantly affect battery endurance. This sensitivity motivates explicitly modeling battery feasibility and endurance-related constraints, as done in this study.

Nevertheless, implementing this operational paradigm presents substantial computational and modeling challenges. Coordinating heterogeneous fleets requires addressing the coupled spatiotemporal dependencies inherent in vehicle routing. Delivery schedules must strictly account for payload capacity, battery limitations, and delivery time windows while simultaneously synchronizing truck routes with UAV launch and recovery operations. Moreover, these systems involve complex multi-criteria trade-offs among operational safety, energy sustainability, service levels, and cost-effectiveness [8]. These difficulties are further intensified by the integration of emerging aviation regulations, such as the Specific Operations Risk Assessment (SORA). This framework mandates the evaluation of airspace risk and ground population exposure during UAV deployment planning [9]. Traditional exact methods struggle to scale with these complexities, while pure heuristics often fail to guarantee compliance with strict energy and safety constraints.

When applied to this complex problem space, traditional optimization techniques, such as heuristic-only procedures and formulations based solely on MILP, frequently fall short, particularly as delivery networks expand. Exact techniques are rapidly rendered impractical due to the high computational cost of simultaneously optimizing drone assignments and truck routes over large customer sets while satisfying regulatory and energy constraints [10]. Conversely, purely heuristic approaches often lack the precision required to guarantee feasibility under strict risk and energy constraints. These limitations have driven the development of hybrid optimization methods, which combine the scalability of metaheuristics with the structural rigor of exact approaches [11].

A recent review has highlighted a critical gap in the literature, namely the limited integration of regulatory constraints and realistic safety barriers into automated logistics optimization models [12]. Although many studies optimize truck–drone collaboration for cost or service reliability, they often abstract away operational safety, airspace restrictions, and deployment-oriented constraints that arise in real urban environments [13]. This limitation is particularly consequential because recent evidence [14] suggests that ignoring spatial restrictions, such as no-fly zones and vehicle-restricted areas, can yield routing plans that become infeasible when implemented in complex city settings.

Recent surveys highlight that the adoption and maturity of UAV-based last-mile delivery vary widely across countries and regions. While pilot deployments and commercial trials are underway in North America, parts of Europe, and East Asia, large-scale operational integration remains limited in many jurisdictions because of differing regulatory regimes, infrastructure readiness, and public acceptance concerns. In particular, the work of [15] synthesizes optimization challenges in last-mile logistics and emphasizes how urban constraints and local policy shape feasible routing models, whereas [16] reviews operational variants of last-mile delivery and shows that heterogeneity in regulation and market structure strongly affects which algorithmic and deployment choices are practical. Such disparities underscore the need for optimization frameworks that are not only computationally efficient but also explicitly aligned with aviation regulations and safety assessment methodologies.

To address these gaps, this study proposes a scalable, risk-aware framework for the multi-objective Truck–Drone Delivery Problem (TDDP). We introduce a novel model that simultaneously minimizes four key objectives: transportation costs, service time (with soft time windows), energy consumption, and a SORA-based operational risk index. To ensure computational tractability without sacrificing solution quality, we employ a two-phase matheuristic that couples MILP-based drone scheduling with heuristic route construction.

The selection of these four objectives is motivated by both practical relevance and gaps identified in the existing literature. Transportation cost and service time remain the most commonly adopted performance indicators in last-mile delivery, reflecting operational efficiency and customer service requirements [16]. Energy consumption is explicitly included to capture the limited endurance of UAVs and the growing emphasis on sustainability in drone-assisted logistics, as highlighted in recent studies on battery-constrained UAV operations [15]. In addition, a SORA-based operational risk objective is incorporated to explicitly reflect regulatory compliance and safety considerations, which are often neglected or only implicitly addressed in existing truck–drone routing models.

While other objectives, such as emissions, equity, or platform coordination, could also be considered, incorporating an excessive number of objectives would significantly reduce interpretability and computational tractability in large-scale multi-objective optimization. The selected four objectives, therefore, represent a balanced and complementary set that jointly captures economic efficiency, service quality, energy sustainability, and regulatory safety, aligning with both real-world planning priorities and current methodological capabilities.

The main contributions of this work are as follows:

- A comprehensive multi-objective TDDP model incorporating soft time windows, precise battery constraints, energy costs, and risk assessments;
- A novel matheuristic framework that integrates MILP-guided subproblem solving within a multi-objective metaheuristic structure;
- Extensive computational experiments on synthetic delivery networks of varying sizes (20, 50, and 100 customers) demonstrate the model’s scalability and optimization quality;
- A detailed structural and sensitivity analysis that evaluates the impact of drone endurance, availability, and velocity on system performance.

The remainder of this article is organized as follows: Section 2 reviews the relevant literature on multi-objective optimization in last-mile delivery, truck–drone collaboration models, and the integration of regulatory constraints. Section 3 details the materials and methods, including the mathematical formulation of the four-objective TDDP, the system assumptions, and the proposed two-phase matheuristic solution approach. Section 4 presents the computational results, demonstrating the framework’s performance across varying network sizes and configurations. Section 5 discusses these findings, analyzing the trade-offs between cost, service time, energy, and operational risk. Finally, Section 6 provides the conclusions and outlines potential directions for future research.

2. Literature Review

This section reviews the foundational and recent literature relevant to the TDDP. It is organized into five subsections: (1) Classical Vehicle Routing Problems (VRP), (2) Truck–Drone Collaboration Models, (3) Multi-Objective Optimization in Last-Mile Delivery, (4) Risk and Energy Constraints in UAV Logistics, and (5) Research Gaps and Novelty of This Work.

2.1. Classical Vehicle Routing Problems

For decades, the VRP has been a cornerstone of operations research and transportation science. Rooted in the Traveling Salesman Problem, the VRP focuses on the optimal routing of a fleet of vehicles to serve geographically distributed clients while minimizing total operating costs. Over time, various extensions have been developed to reflect real-world constraints more accurately, such as the Capacitated VRP, VRP with Time Windows [17], and VRP with Pickup and Delivery [18].

To solve these increasingly complex problems, metaheuristic approaches have gained popularity, particularly for large-scale applications where exact methods become computationally prohibitive. Algorithms such as NSGA-II, Tabu Search, Genetic Algorithms, and Simulated Annealing have effectively explored complex routing spaces; for example, ref. [19] adapts evolutionary strategies to improve Pareto-front coverage, while ref. [20] employs neighborhood-based hybrid heuristics to speed convergence and enhance solution quality. These methods enable decision-makers to evaluate trade-offs between conflicting objectives, such as cost reduction and maximizing service levels.

Hybrid vehicle-drone VRPs represent a significant evolution of the classical VRP formulation. Initial research by [21,22] established the groundwork for integrating UAVs into routing systems. To manage the increased complexity of these hybrid systems, ref. [23] introduces matheuristic and adaptive large neighborhood search (ALNS) approaches that combine exact optimization with heuristic search for large-scale routing problems, while ref. [24] demonstrates the effectiveness of hybrid exact–heuristic methods for solving complex vehicle routing problems under realistic constraints.

Despite these advancements, conventional VRP models often fail to account for the unique challenges of UAV-based systems, such as asynchronous scheduling, dual-layer mobility, and risk-aware regulations. Drone operations involve specific airspace restrictions, safety risks, and energy constraints that traditional formulations cannot adequately manage. Building on the SORA framework, this study expands the fundamental VRP to a hybrid truck–drone environment, explicitly integrating energy consumption, safety restrictions, and regulatory compliance.

2.2. Truck–Drone Collaboration Models

The integration of drones into last-mile logistics has motivated new optimization problems that explicitly capture truck–drone coordination and synchronization. The seminal study by ref. [21] introduces the Flying Sidekick Traveling Salesman Problem (FSTSP), formalizes coordinated truck–drone decisions, and presents an MILP formulation that minimizes the overall completion time (makespan). Building on this foundation, ref. [25] investigates a hybrid vehicle–drone delivery setting aimed at improving last-mile completion efficiency through integrated routing and sortie planning, while ref. [26] further extends the truck–drone paradigm by modeling how drone routing and synchronization interact with system-level operating costs in congested low-altitude airspace.

As noted by ref. [2], early studies on truck–drone delivery typically relied on static settings and simplifying assumptions, such as a single UAV per truck and tightly synchronized operations. Subsequent research has progressively relaxed these assumptions by introducing more realistic coordination structures. For example, ref. [27] examined fundamental truck–drone interaction mechanisms and analyzed how drone launches and recoveries can be coordinated along a truck route under basic feasibility constraints. Similarly, ref. [28] studied coordinated truck–drone delivery systems with an emphasis on synchronization decisions and routing efficiency, highlighting the impact of coordination strategies on overall system performance. In a related vein, ref. [29] investigated last-mile

delivery with UAV assistance by formalizing launch, service, and rendezvous decisions, thereby clarifying the operational structure of coordinated truck–drone routes.

Building on these foundations, later works incorporate increasingly sophisticated features, including explicit time window management [30], asynchronous scheduling, detailed energy consumption modeling, and the deployment of multiple UAVs per truck [31]. To address the resulting increase in computational complexity, researchers have also proposed scalable solution approaches, such as heuristic algorithms [32] and decomposition-based techniques [33].

However, many existing models remain limited by single-objective formulations or a neglect of operational risks, particularly in urban environments. Addressing the spatial complexities of city logistics, ref. [34] recently proposed a model accounting for urban regional restrictions. While their work effectively manages hard spatial constraints, our study extends this concept by incorporating the SORA framework to quantify the operational risk of traversing specific zones, rather than treating them solely as binary restrictions.

Furthermore, ref. [35] proposes a resilient truck–drone collaboration framework that accounts for time-dependent truck speeds and multi-visit operational structures, but their formulation remains risk-neutral. In contrast, our model incorporates risk awareness directly into routing and scheduling decisions through a SORA-based operational risk index, allowing safety to be co-optimized alongside cost, service time, and energy use. Similarly, while [36,37] address stochastic demand and multi-modal delivery, respectively, our work focuses on the trade-off between strict service-time performance and explicit regulatory risk compliance in truck–UAV operations.

2.3. Multi-Objective Optimization in Last-Mile Delivery

As urban logistics systems become increasingly complex, multi-objective optimization has emerged as a central modeling paradigm for last-mile delivery planning. Decision-makers must simultaneously balance regulatory compliance, environmental sustainability, delivery speed, and cost-effectiveness. In this context, ref. [38] develops a multi-objective truck–drone delivery formulation that explicitly captures trade-offs among competing operational objectives using Pareto-based solution concepts. Complementing this modeling perspective, ref. [39] provides a comprehensive survey of multi-objective approaches in truck–drone logistics, synthesizing the use of scalarization techniques, ϵ -constraint methods, and evolutionary algorithms such as NSGA-II and MOEA/D. More recently, ref. [40] demonstrates how evolutionary multi-objective algorithms can be effectively applied to large-scale truck–UAV routing problems, highlighting their ability to generate diverse high-quality Pareto fronts under realistic operational constraints.

In the context of UAV-enabled logistics, multi-objective optimization has been increasingly adopted to address trade-offs among competing performance criteria. For instance, ref. [41] proposes a hybrid optimization framework that balances delivery time and cost in coordinated truck–UAV operations, demonstrating the benefits of combining exact and heuristic elements. Similarly, ref. [42] formulates a multi-objective UAV-assisted delivery model that emphasizes service efficiency and cost reduction under operational constraints. Focusing on energy-related trade-offs, ref. [43] investigates UAV routing strategies that balance energy consumption and delivery reliability, highlighting the sensitivity of feasible solutions to battery limitations. From a longer-term planning perspective, it introduces a strategic framework for adaptive hybrid RPAS logistics, emphasizing scalability and flexibility in evolving delivery networks. However, these studies rarely combine sustainability and safety indicators within a single framework and often suffer from scalability issues. Purely heuristic methods lack precision, while exact MILP formulations struggle with large instances.

Recent studies have explored advanced methods, such as Multi-Agent Deep Reinforcement Learning [44] and combinatorial auctions [45]. However, these approaches often lack optimality guarantees for sub-problems. Our matheuristic framework bridges this gap by retaining the exactness of MILP for the drone scheduling phase while using a metaheuristic for global routing. By simultaneously minimizing transportation cost, service time (with soft time windows), energy consumption, and operational risk, the proposed model offers a robust tool for optimizing modern last-mile delivery systems.

2.4. Risk and Energy Constraints in UAV Logistics

UAV operations are increasingly constrained by both energy limitations and regulatory risk assessment requirements, making battery feasibility a central consideration in sortie planning. Battery capacity directly affects feasible sortie design, particularly when payload weight, travel distance, and environmental conditions influence energy consumption. In this context, ref. [46] develops analytical energy consumption models that explicitly link UAV power usage to payload and flight distance, while ref. [47] provides a quantitative assessment of UAV energy expenditure under varying operational conditions, including environmental effects. Complementing these approaches, ref. [48] integrates detailed battery consumption models directly into routing formulations, demonstrating that simplified range-based constraints can significantly misrepresent feasibility in realistic delivery scenarios. Reinforcing the need for high-fidelity energy modeling, ref. [49] employs machine learning techniques to predict UAV battery consumption with high accuracy, which motivates the explicit battery-tracking and energy-feasibility constraints adopted in this study.

Simultaneously, regulatory authorities have introduced formal safety assessment frameworks to govern UAV operations in shared airspace. In particular, ref. [50] outlines the principles of the Specific Operations Risk Assessment (SORA), which evaluates mission feasibility based on airspace classification, ground risk exposure, and proximity to third parties. Building on this regulatory foundation, ref. [51] investigates risk-aware UAV routing under restricted airspace conditions, demonstrating how safety considerations can influence feasible trajectories and operational cost. More recently, ref. [52] examines the feasibility of UAV flight under combined design and regulatory constraints, highlighting the limitations of static no-fly-zone representations for capturing real operational risk. While some routing models include static no-fly zones, few have operationalized SORA-based constraints in a dynamic, scalable manner. The proposed approach addresses this by integrating both risk and energy limitations directly into the optimization framework. Drone sorties are evaluated not only for battery feasibility but also for regulatory acceptability using SORA-based metrics. This dual-layered constraint mechanism ensures that generated solutions are both operationally viable and legally compliant.

2.5. Research Gaps and Novelty of This Work

Although recent studies have advanced truck–drone delivery models, important methodological and regulatory gaps persist in the literature. First, most existing models are mono- or bi-objective, failing to address the full spectrum of operational challenges, specifically the interplay between safety risk and energy consumption. For instance, ref. [53] estimates risk in unknown environments to plan safe trajectories for a single drone, but their focus is on local trajectory planning rather than logistics optimization. Building on recent SORA-based UAVs logistics models that jointly optimize cost, time, risk, and battery consumption (e.g., [54]), to the best of our knowledge, there is still no truck–drone last-mile delivery framework that simultaneously optimizes risk, cost, time, and energy in an explicitly SORA-compliant way.

Table 1 provides a comparative overview of the relevant literature, highlighting the objective coverage and methodological choices that motivate the contributions of this study. Second, although multi-objective formulations are increasingly adopted, many existing approaches remain methodologically unbalanced. For example, ref. [55] develops multi-objective optimization frameworks that emphasize Pareto-based exploration but can face scalability limitations when detailed operational constraints are introduced. In contrast, ref. [56] demonstrates the value of exact or tightly structured optimization for multi-criteria routing decisions, yet such approaches can become computationally restrictive as instance size and coordination complexity grow. Third, few studies examine how solutions perform across varying fleet configurations and instance sizes, which limits the generalizability of their results.

Moreover, recent extensions of last-mile delivery models toward joint delivery systems, which combine drones with occasional drivers, crowd-based riders, or mixed on-demand platforms, have primarily focused on cost efficiency, platform coordination, and assignment mechanisms. While these studies contribute valuable insights into collaborative logistics, they typically abstract away aviation-specific constraints, detailed UAV energy consumption, and formal safety or regulatory risk modeling. In particular, risk is often treated implicitly or neglected altogether, and energy considerations are simplified to range constraints or average consumption assumptions.

As a result, these frameworks are not directly applicable to regulated UAV operations, where flight feasibility, safety exposure, and battery limitations must be evaluated simultaneously at the routing and scheduling levels. In contrast, the present study targets regulated truck–drone delivery systems and explicitly models the interaction between routing, UAV energy expenditure, and operational risk exposure. This distinction is fundamental rather than incremental, as it shifts the focus from platform-level coordination to compliance-aware logistics optimization. By embedding SORA-based risk metrics directly into the optimization objectives, alongside cost, service time, and energy consumption, the proposed framework addresses a critical gap that remains insufficiently explored in both classical truck–drone routing models and emerging joint delivery formulations.

This study addresses these limitations by proposing a comprehensive, four-objective optimization model within a scalable matheuristic framework. The novelty of this work lies in:

- **Integrated Methodology:** Combining MILP for precise subproblem solving with a meta-heuristic for global routing to ensure both scalability and solution quality;
- **Realistic Constraints:** Integrating detailed energy modeling, soft time windows, and, crucially, a SORA-based risk assessment;
- **Scalability:** Providing extensive sensitivity and structural analyses to validate the framework across various problem scales and operational settings.

Table 1. Comparison of relevant literature on the TDDP.

Reference	Trucks	Drones	Objective	Method	Vertices
[21]	1	1	Time	MILP, heuristic	10–20
[22]	n	m	Time	Theoretical Insights	10–50
[29]	n	m	Time	MILP	5–10
[57]	1	1	Time	IP, DP, heuristic	10–100
[28]	1	m	Time	Heuristic	25–500

Table 1. *Cont.*

Reference	Trucks	Drones	Objective	Method	Vertices
[33]	1	1	Time	Heuristic	10–20
[27]	1	m	Time	MILP, SA	5–100
[32]	1	1	Cost/Time	MILP, GRASP	10–100
[23]	n	1	Time	MILP, ALNS	6–200
[24]	n	m	Time	MILP, Matheuristic	10–50
[43]	n	m	Cost/Time/Risk	Hybrid MO	10–100
[11]	n	m	Time	Exact/Heuristic	10–50
[52]	n	m	Cost/Time/Risk	Robust Opt.	10–100
[10]	n	m	Time	Heuristic	10–100
[48]	n	m	Cost/Time/Risk	BBN + RL	10–100
[40]	n	m	Cost/Time/Risk	MOEA Ensemble	10–100
[54]	n	m	Cost/Time/Risk	RL	25–500
[17]	n	m	Cost/Time/Risk	Evolutionary	10–100
[20]	n	m	Time	HGA	10–100
[19]	n	m	Cost/Time/Risk	NSGA-II	10–100
[25]	n	m	Time	MILP	10–200
[26]	n	m	Cost/Time/Risk	MILP	10–100
[50]	n	m	Time	Impact-based	25–200
[51]	n	m	Time	Bayesian	10–100
[56]	n	m	Cost/Time	Exact/Heuristic	10–50
[3]	n	m	Cost/Time/Risk	Heuristic	10–100
[2]	n	m	Cost/Time/Risk	MILP	10–100
[9]	n	m	Time/Cost/Risk/Energy	NSGA-II + BBN	10–100
[18]	n	m	Cost/Time/Risk	Stochastic LP	25–200
[31]	n	m	Cost/Time/Risk	MILP	10–50
[30]	n	m	Cost/Time/Risk	Heuristic	10–100
[38]	n	m	Cost/Time/Risk	Stochastic IP	10–100
[39]	n	m	-	Survey	10–100
[41]	n	m	Cost/Time/Risk	Hybrid Heuristic	10–100
[42]	n	m	Time/Cost/Risk/Energy	MO	10–100
[2]	n	m	Cost/Time/Risk	Heuristic	10–100
[47]	n	m	Time	Quantitative	10–100
[55]	n	m	Time	Exact/Heuristic	10–50
[8]	n	m	Cost/Time/Risk	Hybrid	25–200
This Study	n	m	Time/Cost/Risk/Energy	Matheuristic (MILP+NSGA-II)	10–100

3. Materials and Methods

This section details the mathematical formulation of the Multi-Objective Truck–Drone Delivery Problem, the proposed hybrid matheuristic solution approach, and the experimental setup used to validate the framework.

To clarify the structure and execution flow of the proposed hybrid optimization framework, Figure 1 presents a schematic overview of the methodological steps involved in

solving the multi-objective TDDP. The framework integrates a multi-objective evolutionary search for truck routing with an exact MILP subproblem for UAV assignment and scheduling. The process starts with the initialization of input data and model parameters, followed by the generation of non-dominated truck routes using an NSGA-II-based procedure. For each candidate truck route, a MILP-based module assigns and schedules UAV sorties while explicitly enforcing energy feasibility and SORA-based operational risk constraints. Infeasible or dominated solutions are filtered through a Pareto archive update mechanism, ensuring convergence toward high-quality non-dominated solutions. This iterative interaction between heuristic exploration and exact feasibility enforcement provides both scalability and regulatory compliance, offering a transparent overview of how the proposed combined model is developed and applied.

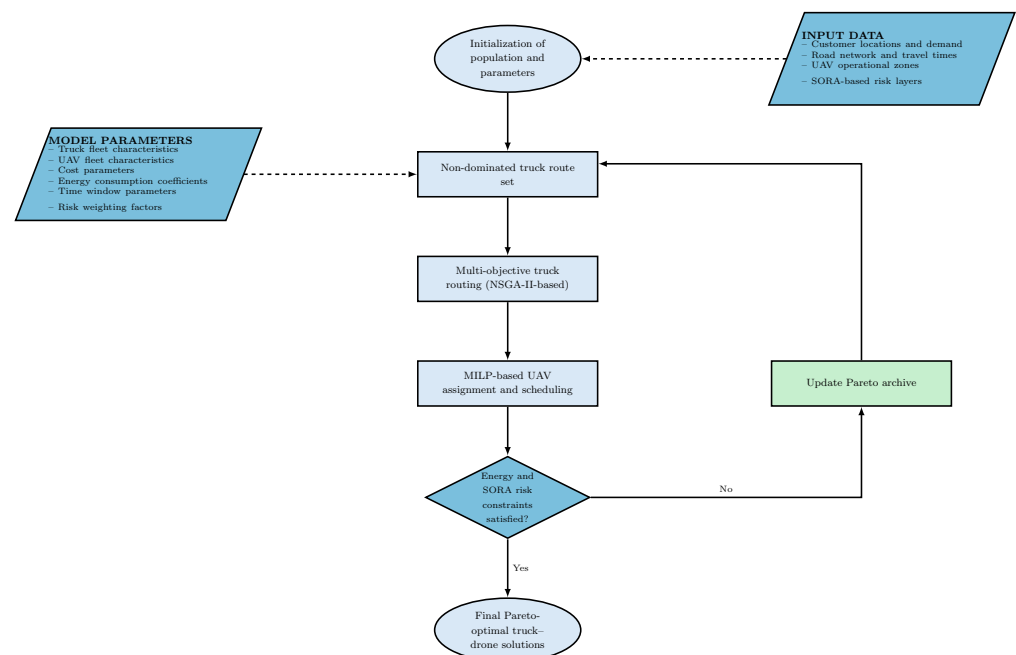


Figure 1. Methodological scheme of the proposed hybrid MILP-NSGA-II framework for the risk-aware truck–drone delivery problem.

3.1. Problem Description

The problem is modeled as a coordinated truck–drone delivery network where a fleet of trucks, each equipped with one or more drones (UAVs), departs from a central depot to serve a set of geographically distributed customers. The objective is to simultaneously minimize four conflicting criteria: (1) total transportation cost, (2) service time (including soft time window penalties), (3) energy consumption, and (4) operational risk based on the SORA framework. The following assumptions govern system operation:

- Integrated truck–drone delivery: Each UAV performs one delivery per sortie, departing from the truck at a launch node, traveling to a customer, and returning either to the truck’s later location or the final depot.
- Synchronization: UAVs must launch and land at locations and times consistent with the truck’s route schedule. The truck cannot depart from a launch node until all active UAV assignments are completed.
- Energy and battery limits: UAV flight endurance, minimum return charge, and charging possibilities are captured through dynamic battery-level constraints. Energy consumption is influenced by various factors, including distance, speed, payload, and environmental conditions.

- Time windows: Deliveries are assigned both hard time windows (mandatory) and soft time windows (violations allowed but penalized). Early or late deliveries incur penalty costs.
- SORA-based risk modeling: Operational risks associated with UAV flight paths are quantified using the SORA, incorporating ground population density, airspace type, and no-fly risk-intense zones.
- Multi-objective optimization: The problem minimizes simultaneously: (i) transportation cost, (ii) service time and soft-window penalties, (iii) SORA-based operational risk, and (iv) energy-related expenditures.
- Single-customer UAV deliveries: Each UAV can serve only one customer during each sortie and must return to its base before being dispatched again.

This operational setting yields a tightly coupled spatiotemporal routing and scheduling problem requiring advanced modeling and solution techniques.

3.2. Mathematical Model

This section defines the essential sets, parameters, and decision variables used in the optimization model. The sets describe the structural elements of the problem, including distributor locations, pickup nodes, service nodes, and subsets related to the UAV. Together, these definitions establish the operational environment and provide the foundation for formulating the mathematical objectives and constraints of the truck–drone delivery system. The model's detailed notations, sets, parameters, and variables are included in Appendix A at the end of this study due to the extensive nature of the notations and explanations.

To improve readability and facilitate interpretation of the proposed multi-objective formulation, Table 2 provides a concise summary of the four objective functions alongside their mathematical expressions and intuitive descriptions. This table is intended to guide readers through the optimization goals before engaging with the detailed formulation presented in Equations (1)–(4).

Table 2. Summary of the four objective functions in the multi-objective truck–drone delivery model.

Equation	Objective	Plain-Language Interpretation
(1)	Minimize total operational cost	Minimizes the combined transportation cost of truck routes and UAV sorties, including fixed deployment and variable travel-related costs.
(2)	Minimize service time deviation	Minimize the deviation from customer time windows using soft penalties to capture service quality degradation.
(3)	Minimize UAV energy consumption	Minimizes total UAV energy usage, accounting for flight distance, payload-dependent consumption, and endurance limitations.
(4)	Minimize operational risk (SORA-based)	Minimizes aggregated SORA-based operational risk by considering ground risk exposure along UAV flight paths.

As shown in Equation (1), the first objective function, Z_1 , minimizes the total transportation-related cost. This includes operating costs for trucks and UAVs, fixed deployment costs for UAVs, infrastructure costs for establishing distribution centers at candidate locations, and preparation costs incurred at pickup nodes.

$$\begin{aligned}
Z_1 = \min & \sum_{i \in N_0} \sum_{j \in N_+} \sum_{tr \in TR} x_{ij}^{tr} \cdot C_{ij} + \sum_{i \in N_0} \sum_{j \in N'} \sum_{B \in B} \sum_{tr \in TR} y_{ijB}^{tr} \cdot C_{ij}^B + \\
& \sum_{i \in N_0} \sum_{j \in N'} \sum_{k \in K} \sum_{tr \in TR} SA_{ij}^{tr} \cdot f_{iy_k} + \\
& \sum_{i \in N_0} \sum_{j \in N'} \sum_{d \in D, f \in F} \sum_{tr \in TR} SA_{ij}^{tr} (fix_d + Cp_f \cdot L_i^{tr})
\end{aligned} \quad (1)$$

The second objective function, Z_2 , defined in Equation (2), aims to minimize the total service time, along with the penalties incurred for violating the soft time window constraints.

$$Z_2 = \min \sum_{i \in N} \alpha \cdot es_i + \beta \cdot ls_i + \sum_{tr \in TR} t_i^{tr} + \sum_{tr \in TR} t_i^{tr} \quad (2)$$

The third objective function, Z_3 , defined in Equation (3), is formulated to minimize a SORA-based operational risk index. For nodes i and j in the set $P \cup D$, the model evaluates the routing risk of traversing each arc (i, j) and aggregates these values into a global index, computed as the maximum of the accumulated risk over all such arcs. Each arc risk is expressed as a weighted sum of several contributing factors (e.g., ground population density, airspace class, proximity to sensitive areas), following the weighting scheme proposed by ref. [52], which is derived from the SORA standard developed by JARUS. In line with SORA, the index in Equation (3) explicitly accounts for both ground risk (risks to people on the ground) and air risk (risks to other airspace users).

$$\begin{aligned}
Z_3 = \text{minimax} & \sum_{i, j \in N_0 \cup N', B \in N_+, tr \in TR} s_{ij}^{tr} (y_{ijB}^{tr} + x_{ij}^{tr}) + \\
& \sum_{i, j \in N_0 \cup N', tr \in TR, k \in K} s_{ij}^k \cdot SA_{ij}^{tr}
\end{aligned} \quad (3)$$

The fourth objective function, Z_4 , shown in Equation (4), seeks to minimize the total cost associated with energy use and UAV assets. Specifically, it aggregates (i) the cost of energy consumption, (ii) the investment and operational costs of the UAVs, and (iii) the costs associated with battery usage and degradation. The purpose of this objective is to ensure that all customer orders are served within the planning horizon in an energy-efficient and asset-efficient manner, while still respecting the designated pickup time windows.

$$\begin{aligned}
Z_4 = \min & \sum_{i, j \in N_0 \cup P} \sum_{B \in N_+} C_E \cdot C_{ij}^k \cdot y_{ijB}^{tr} + \\
& \sum_{i, j \in N_0 \cup P, B \in N_+} \left(C_k + \frac{C_L}{n_k} + C_k^M \right) y_{ijB}^{tr} + \\
& C_{en} \sum_{tr \in T} \left(ch_K^0(tr) - g_{2n+1}^{tr} \right)
\end{aligned} \quad (4)$$

Subject to:

$$\sum_{B \in N_+} \sum_{j \in N'} \sum_{i \in N_0} y_{ijB}^{tr} + \sum_{B \in N_+} \sum_{j \in N'} \sum_{i \in N_0} x_{ij}^{tr} = 1, \forall j \in \phi \quad (5)$$

$$\sum_{j \in N_+} x_{0j}^{tr} \leq 1 \quad \forall tr \in TR \quad (6)$$

$$\sum_{j \in N_0} x_{i, 2n+1}^{tr} \leq 1 \quad \forall tr \in TR \quad (7)$$

$$1 + po_i^{tr} - po_j^{tr} \leq (1 - x_{ij}^{tr})(2n + 2) \quad \forall i \in \phi, j \in \{N_+, j \neq i\}, tr \in TR \quad (8)$$

$$\sum_{i \in N_0} x_{ij}^{tr} = \sum_{i \in N_+} x_{ji}^{tr} \quad \forall j \in \phi, tr \in TR \quad (9)$$

$$\sum_{j \in \phi} \sum_{B \in N_+} y_{ijB}^{tr} \leq 1, \forall i \in N_0, tr \in TR \quad (10)$$

$$\sum_{j \in \phi} \sum_{i \in N_0} y_{ijB}^{tr} \leq 1, \forall B \in N_+, tr \in TR \quad (11)$$

$$y_{ijB}^{tr} \leq \sum_{h \in N_0} x_{hi}^{tr} + \sum_{h \in N_0} x_{iB}^{tr}, \quad \forall i \in N', B \in N_+ \quad (12)$$

$$y_{0jB}^{tr} \leq \sum_{h \in N_0} x_{hB}^{tr}, \quad \forall j \in N', B \in N_+ \quad (13)$$

$$po_B^{tr} - po_i^{tr} \geq 1 - (2n + 2)(1 - \sum_{j \in \phi} y_{ijB}^{tr}) \quad (14)$$

$$t_i^{tr} \geq t_i^{tr} - M \left[1 - \sum_{i \in N'} \sum_{j \in P} y_{ijB}^{tr} \right], \quad \forall B \in N_+ \quad (15)$$

$$t_i^{tr} \leq t_i^{tr} + M \left[1 - \sum_{i \in N'} \sum_{j \in P} y_{ijB}^{tr} \right], \quad \forall B \in N_+ \quad (16)$$

$$t_i^{tr} \geq t_i^{tr} - M \left[1 - \sum_{i \in N'} \sum_{j \in P} y_{ijB}^{tr} \right], \quad \forall B \in N_+ \quad (17)$$

$$t_i^{tr} \leq t_i^{tr} + M \left[1 - \sum_{i \in N'} \sum_{j \in P} y_{ijB}^{tr} \right], \quad \forall B \in N_+ \quad (18)$$

$$\begin{aligned} t_i^{tr} &\geq t_i^{tr} + \tau_{hB} + D_h^{tr} \\ &+ SL_B \sum_{n \in N', \notin B} \sum_{m \in N_+} y_{Bnm}^{tr} \\ &+ SR_B \sum_{n \in N_0, \notin B} \sum_{j \in N'} y_{ijn}^{tr}, \quad \forall h \in N_0, k \in \{N_+, B \notin h\} \end{aligned} \quad (19)$$

$$t_j^{tr} \geq t_i^{tr} + \pi_{ij}^k - M \left[1 - \sum_{B \in N_+} y_{ijB}^{tr} \right] \quad (20)$$

$$t_B^{tr} \geq t_j^{tr} + \pi_{jB}^k + D_j^k - M \left[1 - \sum_{i \in N_0} y_{ijB}^{tr} \right] \quad (21)$$

$$t_B^{tr} - (t_i^{tr} - \tau_{hB}) \leq e + M \left[1 - y_{ijB}^{tr} \right], \quad \forall B \in N_0, j \in N', j \neq B, tr \in TR \quad (22)$$

$$po_i^{tr} - po_j^{tr} \geq 1 - (2n - 2)SA_{ij}^{tr}, \quad \forall i, j \in N', j \neq i, tr \in TR \quad (23)$$

$$po_i^{tr} - po_j^{tr} \leq -1 + (2n - 2)(1 - SA_{ij}^{tr}), \quad \forall i, j \in N', j \neq i, tr \in TR \quad (24)$$

$$SA_{ij}^{tr} + SA_{ji}^{tr} = 1, \quad \forall i, j \in N', j \neq i, tr \in TR \quad (25)$$

$$t_l^{tr} \geq t_k^{tr} - M \left[3 - \sum_{j \in \phi, \neq l} y_{Bhj}^{tr} - \sum_{m \in \phi, \neq i, k, l} \sum_{n \in N_+, \neq i, k} \right], \quad (26)$$

$$\forall i \in N_0, B \in N_+, B \neq i, l \in \phi, \neq i, B, tr \in TR$$

$$L_j^{tr} \geq L_i^{tr} + Lo_j + \sum_{h \in F} \sum_{B \in N_0} Lo_h y_{Bhj}^{tr} + \sum_{h \in F} \sum_{B \in N_+} Lo_h y_{jBh}^{tr} - M \left[1 \cdot x_{ij}^{tr} \right] \quad (27)$$

$$L_0^{tr} = 0, \quad \forall tr \in TR \quad (28)$$

$$y_{2n+1,jB}^{tr} = 0, \quad \forall j \in N, tr \in TR \quad (29)$$

$$t_i^{tr} \leq T_{max}, \quad \forall i \in N, tr \in TR \quad (30)$$

$$t_i'^{tr} \leq T_{max}, \quad \forall i \in N, tr \in TR \quad (31)$$

$$L_i^{tr} \leq cap, \quad \forall j \in N, tr \in TR \quad (32)$$

$$Es_i \geq E1_i - \sum_{tr \in TR} t_i^{tr} - M \left[1 - \sum_{j \in \phi, tr \in TR} x_{ij}^{tr} \right], \quad \forall i \in \phi \quad (33)$$

$$Es_i \geq E1_i - \sum_{tr \in TR} t_i'^{tr} - M \left[1 - \sum_{j \in \phi, tr \in TR, B \in N} y_{ijB}^{tr} \right], \quad \forall i \in \phi \quad (34)$$

$$Ls_i \geq \sum_{tr \in TR} t_i^{tr} - L1_i - M \left[1 - \sum_{j \in \phi, tr \in TR} x_{ij}^{tr} \right], \quad \forall i \in \phi \quad (35)$$

$$Ls_i \geq \sum_{tr \in TR} t_i'^{tr} - L1_i - M \left[1 - \sum_{j \in \phi, tr \in TR, B \in N} y_{ijB}^{tr} \right], \quad \forall i \in \phi \quad (36)$$

$$g_j^{tr} \geq g_i^{tr} - en_{ij} (1 - x_{ij}^{tr}) - \sum_{l \in N} \sum_{B \in N} (en_{Bl} + en_{lj}) y_{Blj}^{tr} - M \left[1 - \sum_{B \in N} y_{ijB}^{tr} - x_{ij}^{tr} \right], \quad (37)$$

$\forall i, j \in N, i \neq j, tr \in TR$

$$g_o^{tr} = ch0^{tr}, \quad \forall i \in N, tr \in TR \quad (38)$$

$$g_i^{tr} \geq chmin^{tr}, \quad \forall i \in N, tr \in TR \quad (39)$$

$$g_i^{tr} \leq chmax^{tr}, \quad \forall i \in N, tr \in TR \quad (40)$$

$$x_{ii}^{tr} = 0, \quad \forall i \in N, tr \in TR \quad (41)$$

$$y_{iiB}^{tr} = 0, \quad \forall i \in N, B \in N, tr \in TR \quad (42)$$

$$y_{iBB}^{tr} = 0, \quad \forall i \in N, B \in N, tr \in TR \quad (43)$$

$$y_{0iB}^{tr} = 0, \quad \forall i \in N, B \in N, tr \in TR \quad (44)$$

$$y_{i0B}^{tr} = 0, \quad \forall i \in N, B \in N, tr \in TR \quad (45)$$

$$ES_i \leq T_{max}, \quad \forall i \in N, tr \in TR \quad (46)$$

$$LS_i \leq T_{max}, \quad \forall i \in N, tr \in TR \quad (47)$$

The optimization model for the truck–drone last-mile delivery problem is characterized by 47 constraints, grouped into five functional categories: routing, time windows, load and capacity, battery and energy, and risk and safety.

- Routing constraints (5)–(14)

These constraints define the joint truck–drone routing structure. They ensure that every customer is served exactly once by either a truck or a UAV; each truck departs from and returns to a depot; flow conservation holds at every visited node; and subtours are eliminated. Additional constraints couple truck and UAV routes, guaranteeing that each UAV sortie is compatible with the corresponding truck route, that launch and recovery nodes are visited in the correct sequence, and that each delivery node is assigned to at most one UAV.

- Time-window and synchronization constraints (15)–(24)
These constraints enforce both hard and soft time windows for trucks and UAVs. They bound the earliest and latest allowable service times, limit deviations from soft windows via penalty variables, and synchronize truck departures with UAV launch and recovery operations. Trucks cannot leave a location before their assigned UAV has completed service and returned, and UAVs are prevented from starting service before the associated truck reaches the launch point.
- Load and capacity constraints (25)–(32)
These constraints control truck loading and UAV payloads. They ensure that truck loads never exceed vehicle capacity, that loads are updated consistently after deliveries, and that UAVs do not carry more than their allowable payload. Operating-hour limits on trucks and maximum flight durations for UAVs are also imposed so that total service and travel times remain within feasible operational bounds.
- Battery and energy constraints (33)–(41)
These constraints govern the energy usage and recharging of UAVs. They require a sufficient state of charge before launch and between charging points, model battery consumption along sorties, and enforce minimum and maximum charging levels at recharging stations. Additional constraints limit discharge rates, allow for energy-saving behavior over longer operations, and prevent trucks from waiting indefinitely for UAV recharging.
- Risk and safety constraints (42)–(47)
These constraints incorporate SORA-based risk considerations and airspace regulations. They restrict UAV flights through high-risk or restricted zones, impose minimum separation between truck routes and UAV trajectories, and prohibit landings at unapproved locations. Emergency rerouting rules are also included to handle battery anomalies or sudden airspace restrictions.

Together, constraints (5)–(47) define a feasible and safe operating region for the model, ensuring that the optimized truck–drone delivery plans remain operationally realistic while balancing cost, service time, energy consumption, and risk.

For completeness, Appendix A provides the complete notation, including all decision variables, parameters, and auxiliary quantities used in the formulation. Every symbol appearing in objective functions (1)–(4) and the associated constraints is explicitly defined there, with auxiliary variables introduced for feasibility enforcement and energy/battery tracking clearly identified.

3.3. Proposed Solution Approach

Traditional optimization strategies become ineffective for medium- and large-scale instances of the four-objective TDDP, particularly when battery constraints, SORA-based risk indices, energy-related costs, and both hard/soft time windows are considered. Although MILP can yield optimal solutions for small instances, its computational burden grows rapidly with problem size due to the high-dimensional decision space and non-linear interactions among the objectives. To address these challenges, a multi-objective matheuristic approach is adopted. This method combines exact MILP optimization for drone assignment and scheduling with heuristic procedures for truck routing and initial allocation. The framework is specifically designed to satisfy all operational constraints while handling the trade-offs among cost, service time, safety risk, and energy expenditures. The main motivations for using this solution approach are as follows:

- Decomposition of complexity: The original problem is decomposed into two subproblems—truck routing and drone scheduling—reducing computational complexity and increasing modeling flexibility.

- Effectiveness in multi-objective optimization: Evolutionary algorithms are employed in the routing phase to explore trade-offs among multiple objectives, while the scheduling phase relies on MILP to refine solutions under detailed operational constraints.
- Scalability for real-world scenarios: The combined heuristic–exact structure produces high-quality solutions within practical computation times, making it suitable for large-scale delivery systems.

The proposed framework thus integrates scenario-based risk modeling, multi-layered decision-making, and energy-aware logistics planning. The following subsections provide a detailed description of the overall architecture, its two main phases, and the computational enhancements used to improve performance.

3.3.1. Overall Hybrid Matheuristic Framework

The proposed matheuristic framework decomposes the complex TDDP into two sequential yet interdependent phases. The first phase focuses on generating feasible truck routes and an initial allocation of deliveries using a multi-objective routing heuristic. The second phase refines these routes by solving a tailored MILP-based Drone Assignment and Scheduling Problem (DASP), which explicitly accounts for battery usage, energy costs, delivery windows, and SORA-based risk indices. The overall framework proceeds through the following structured steps:

Step 1: Initialization

- Generate initial delivery routes using NSGA-II or a randomized savings heuristic.
- Produce a diverse set of routing solutions that capture different trade-offs among the four objectives (cost, time, energy, risk).

Step 2: Evaluation

- Evaluate each routing solution using a multi-objective scorecard (cost, time, energy, risk).
- Eliminate infeasible and strictly dominated routes.

Step 3: Drone Assignment and Scheduling (DASP)

- For each selected truck route, construct an MILP model to determine the optimal assignments of UAVs and sortie schedules.
- Incorporate detailed constraints on battery dynamics, soft time windows, energy consumption, and risk mitigation.

Step 4: Solution Selection and Archive Management

- Store all feasible MILP-enhanced solutions in a Pareto archive.
- Maintain and update the archive to keep only non-dominated solutions over successive iterations.

Step 5: Local Search and Iteration

- Apply local search operators (e.g., 2-opt, node relocation, string exchange) to improve route structure and diversify the solution set.
- Use dominance-based filtering, tabu mechanisms, and MILP refinement to re-assess improved routes and repeat Steps 2–4 until a stopping criterion (convergence or time limit) is reached.

This integrated heuristic–exact architecture strikes a balance between computational efficiency and multi-objective solution quality, making it suitable for complex, real-world truck–drone delivery systems. Algorithm 1 shows the Pseudo-code of the proposed hybrid matheuristic for multi-objective TDDP. By combining randomized constructive heuristics, local search, tabu-based diversification, and dominance-driven selection, the framework maintains feasibility across multiple dimensions, including cost, time, energy consumption,

and operational risk, while offering decision-makers a rich set of non-dominated solutions in the final Pareto archive.

Algorithm 1 Hybrid Matheuristic Framework for Multi-Objective Truck–Drone Routing

Require: Set of customer nodes N , set of trucks TR , set of UAVs K , set of feasible UAV sorties TP , model parameters $Param$

Ensure: Pareto archive A of non-dominated solutions

```

1: Initialize Pareto archive  $A \leftarrow \emptyset$ 
2: Initialize incumbent solution  $x^* \leftarrow \emptyset$ 
3: Initialize scalarized incumbent value  $f(x^*) \leftarrow +\infty$ 
4: Initialize Tabu list  $TabuList \leftarrow \emptyset$ 
5: while stopping criterion is not satisfied do
6:   Phase 1: Truck routing and initial allocation
7:    $Routes \leftarrow \text{RANDOMIZEDSAVINGSHEURISTIC}(N, TR, Param)$ 
8:    $Routes \leftarrow \text{LOCALSEARCH}(Routes)$  {e.g., 2-opt, relocation, exchange}
9:    $Routes \leftarrow \text{SORTBYDOMINANCEORRANK}(Routes)$  {multi-objective ordering}
10:  for each route  $\pi \in Routes$  do
11:    if  $\pi \in TabuList$  then
12:      continue {skip recently explored routes}
13:    end if
14:    Phase 2: Drone Assignment and Scheduling (DASP)
15:     $x_\pi \leftarrow \text{SOLVEDASP}(\pi, TP, Param, BestObjStop, Cutoff)$ 
16:    if  $x_\pi$  is feasible then
17:       $\text{UPDATEPARETOARCHIVE}(A, x_\pi)$  {keep only non-dominated solutions}
18:      if  $f(x_\pi) < f(x^*)$  then
19:         $x^* \leftarrow x_\pi$ 
20:         $f(x^*) \leftarrow f(x_\pi)$ 
21:      end if
22:    end if
23:     $TabuList \leftarrow \text{UPDATETABULIST}(TabuList, \pi)$ 
24:  end for
25:   $Routes \leftarrow \text{DIVERSIFY}(Routes)$  {e.g., mutation/perturbation operators}
26: end while
27: return  $A$ 

```

3.3.2. Operational Details of the Combined Matheuristic Framework

The steps are shown in Algorithm 1, are organized into two main phases within our framework, as detailed below:

Phase 1 of the proposed framework employs a population-based multi-objective search strategy inspired by the principles of the non-dominated sorting genetic algorithm II (NSGA-II), combined with a randomized savings heuristic and local improvement operators, to generate diverse and feasible truck routing solutions. This phase focuses on exploring alternative truck routing structures that reflect trade-offs among the transportation cost, service time, energy consumption, and operational risk. In all computational experiments, the population size was set to 100 candidate routing solutions. Crossover and mutation operators were applied with probabilities of 0.9 and 0.1, respectively, to promote solution diversity. The algorithm was executed for a maximum of 300 iterations and terminated earlier if no improvement in the Pareto archive was observed over 30 consecutive iterations. Each individual solution in Phase 1 encodes a complete set of truck routes that satisfy vehicle capacity constraints and basic time-window feasibility. Initial solutions are generated using a randomized savings-based heuristic, followed by local search refinement procedures such as 2-opt, relocation, and exchange moves. Pareto dominance and diversity criteria are then used to rank and select promising routing solutions.

At the end of Phase 1, a subset of high-quality, non-dominated truck routing solutions is retained. These selected truck routes are subsequently fixed and passed as inputs to Phase 2, where drone-related decisions are optimized. Specifically, the truck routes determine the feasible launch and recovery points for UAV sorties, as well as the temporal structure within which drone operations must be synchronized. Phase 2 addresses the Drone Assignment and Scheduling Problem (DASP) through an exact mixed-integer linear programming (MILP) formulation. For each selected truck routing solution, the MILP optimally assigns customers to UAVs and schedules their launches and recoveries while accounting for battery endurance limits, energy consumption, hard and soft time windows, and SORA-based operational risk constraints. This sequential decomposition allows the exact MILP to refine UAV-level decisions while preserving the routing structure generated in Phase 1. While Phase 1 relies on Pareto dominance principles to promote routing diversity, scalarization is employed exclusively within the MILP-based DASP to efficiently resolve drone assignment and scheduling decisions.

3.3.3. MILP Formulation of the Drone Assignment and Scheduling Problem (DASP)

The second phase of the proposed framework focuses on the Drone Assignment and Scheduling Problem (DASP), which determines the optimal configuration of UAV sorties for each truck routing solution obtained in Phase 1. For every selected truck route, a dedicated MILP model is constructed to assign delivery nodes to UAVs and schedule their launch and recovery operations. The MILP formulation simultaneously enforces UAV battery endurance constraints, energy consumption limits, hard and soft time-window requirements, SORA-based operational risk restrictions, and synchronization constraints between truck and drone movements. The objective function of DASP minimizes a weighted sum of the transportation cost, service time deviation, operational risk exposure, and energy-related expenditures.

To maintain computational tractability, only a subset of high-quality, non-dominated truck routes generated in Phase 1 is evaluated in Phase 2. The resulting feasible and efficient truck–drone coordination plans are collected, and the non-dominated solutions across all evaluated routes form the final Pareto archive used for decision-making. The scalarized objective function employed in the DASP is formally defined in Equation (48).

$$\begin{aligned} \min Z = & \alpha_1 \sum_{i \in N} \sum_{j \in N} \sum_{tr \in TR} \sum_{B \in TP} Cost_{ijB}^{tr} \cdot y_{ijB}^{tr} + \\ & \alpha_2 \sum_{i \in N} \sum_{k \in K} (T_i^k + TWV_i^k) + \\ & \alpha_3 \sum_{i \in N} \sum_{j \in N} \sum_{tr \in TR} \sum_{B \in TP} Risk_{ijB}^{tr} \cdot y_{ijB}^{tr} + \\ & \alpha_4 \sum_{i \in N} \sum_{j \in N} \sum_{tr \in TR} \sum_{B \in TP} Energy_{ijB}^{tr} \cdot y_{ijB}^{tr} \end{aligned} \quad (48)$$

Subject to:

$$\sum_{j \in N} \sum_{tr \in TR} \sum_{B \in TP} y_{ijB}^{tr} \leq 1 \quad \forall i \in N \quad (49)$$

$$T_j^k \geq T_i^k + ServiceTime_i + FlightTime_{ij}^k - M(1 - Y_{ijB}^{tr}) \quad \forall i, j, k \quad (50)$$

$$T_i^k \geq EarliestTime_i \quad \forall i, k \quad (51)$$

$$T_i^k \leq LatestTime_i + TWV_i^k \quad \forall i, k \quad (52)$$

$$B_j^k \leq B_i^k - \text{BatteryUsage}_{ij}^k + M(1 - y_{ijB}^{tr}) \quad \forall i, j, k \quad (53)$$

$$B_i^k \geq \text{BatteryMinThreshold} \quad \forall i, k \quad (54)$$

$$\sum_{i,j \in N} \text{Risk}_{ijB}^{tr} \cdot y_{ijB}^{tr} \leq \text{Risk}_{max}^{\text{Scenario}} \quad \forall tr \quad (55)$$

$$T_i^k \geq T_{truck}^{tr} (i) \text{ if } i \text{ is a launch or recovery node} \quad (56)$$

Constraints (49)–(56) jointly ensure feasibility across operational, temporal, battery, and risk dimensions. Constraint (49) restricts each customer to at most one UAV sortie. Constraints (50)–(52) enforce both hard and soft delivery time windows, ensuring service schedules remain within acceptable bounds. Battery-related limits in constraints (53) and (54) ensure that UAV sorties remain within available energy capacity. Constraints (55) and (56) bound the overall operational risk in each scenario, and constraint (56) synchronizes UAV launches and recoveries with the truck's presence at the corresponding locations.

The weighted objective function (48), with coefficients $\alpha_1 - \alpha_4$, aggregates four goals into a single measure: (i) transportation and drone deployment costs, (ii) delivery timeliness and soft time-window penalties, (iii) cumulative route risk based on SORA indices, and (iv) energy consumption from battery use and recharging. This algorithm builds and solves an MILP model to assign and schedule UAV sorties within a given truck route under a multi-objective framework. To enhance computational performance, the implementation utilizes Gurobi with valid inequalities and solver settings, including Cutoff and BestObjStop. Algorithm 2 shows the Pseudo-code of the proposed DASP.

3.4. Experimental Setup

The proposed truck–drone framework is evaluated on synthetic last-mile delivery instances defined over a 10×10 km grid, with small, medium, and large test cases containing 20, 50, and 100 customers, respectively. Each instance includes truck stops, candidate launch/recovery points, and customer nodes with hard and soft delivery time windows. Two UAV types with different ranges, energy consumption, and payload capacities are considered, and SORA-based risk scores in $[0.1, 0.9]$ are assigned to nodes and arcs to represent different urban and suburban environments. Cost parameters encompass truck and drone operation, launch/recovery, distribution center setup, and energy use, with battery consumption modeled dynamically and minimum reserve thresholds enforced. For statistical robustness, each scenario is replicated over multiple randomized instances with varying node locations, time windows, and risk profiles.

All experiments are conducted on a Windows 11 workstation with an Intel Core i7-12700K CPU and 32 GB RAM. The MILP components are implemented in Python 3.10 and solved using Gurobi 10.0.1 via its Python API, leveraging features such as Cutoff, BestObjStop, and valid inequalities to strike a balance between runtime and solution quality. The NSGA-II-based routing phase is implemented using the DEAP framework, with tailored local search operators (e.g., 2-opt, node relocation) and Python's multi-processing to solve multiple DASP instances in parallel. Fixed random seeds are used to ensure reproducibility. To systematically assess performance and robustness, scenarios vary customer density (20/50/100 nodes), UAV fleet composition (homogeneous vs. heterogeneous drones), energy limits (battery capacity and consumption rates), and risk profiles (low to high SORA-based exposure), as well as time-window tightness for high-priority customers.

The framework is evaluated using several Key Performance Indicators (KPIs): (i) total transportation cost (trucks, drones, facilities, and energy), (ii) total service time including soft time-window penalties, (iii) aggregate SORA-based risk across all sorties, and (iv) total

energy consumption. Additional diagnostic KPIs include the diversity of solutions in the Pareto archive, the number of feasible drone sorties, and MILP runtime per truck route, providing a comprehensive view of both solution quality and computational behavior.

Algorithm 2 MILP-Based Drone Assignment and Scheduling Problem (DASP)

Require: Truck route π (obtained from Phase 1), set of feasible drone sorties TP , model parameters (battery thresholds, energy costs, time windows, SORA-based risk, etc.)

Ensure: MILP-optimized drone assignment and schedule x_π for route π , or infeasibility flag

Variable definition

2: Define binary variables Y_{ijB}^{tr} for all feasible drone sorties

Define continuous variables:

4: T_i^k for drone arrival time of UAV k at node i

B_i^k for battery level of UAV k at node i

6: TWV_i^k for soft time-window deviation of UAV k at node i

8: **Objective function**

Construct the MILP objective (Equation (48)) to minimize a weighted sum of:

- 10: – routing cost
- service time penalties
- 12: – SORA-based risk index
- energy consumption

14:

Constraints

16: Add assignment constraints (Equation (49)) to ensure each eligible delivery node is served at most once by a UAV

Add time-consistency and service sequencing constraints (Equation (50))

18: Add hard and soft time-window constraints for UAV and truck operations (Equations (51) and (52))

Add battery usage and minimum-reserve constraints (Equations (53) and (54))

20: Add risk-related constraints derived from SORA (Equation (55))

Add synchronization constraints (Equation (56)) coupling UAV operations with truck arrival and departure times along π

22:

MILP solution

24: Configure the MILP solver (e.g., Gurobi) with BestObjStop, Cutoff, time limit, and MIP gap

Optionally add valid inequalities and cuts to tighten the formulation

26: Solve the MILP model

if no feasible solution is found **then**

28: Mark truck route π as infeasible with respect to UAV assignment

return infeasibility flag

30: **else**

Extract UAV assignment variables Y_{ijB}^{tr} and associated timing and battery variables

32: Compute the corresponding objective vector (Z_1, Z_2, Z_3, Z_4) for route π

Construct x_π as the MILP-enhanced solution for route π

34: **return** x_π

end if

4. Results

4.1. Performance of the Hybrid Matheuristic

The proposed matheuristic is designed to balance four conflicting objectives: transportation cost, service time, risk index, and energy consumption. It combines an evolutionary truck-routing heuristic with an exact MILP-based UAV assignment and scheduling model. Together, these components enable the framework to generate high-quality solu-

tions for complex last-mile delivery scenarios that incorporate battery limits, SORA-based risk, and both soft and hard time windows. The framework was tested on multiple instance sizes and operational configurations. In all cases, it produced rich sets of Pareto-optimal solutions that reveal clear trade-offs among the four objectives. The Pareto archive grows steadily over iterations, as shown in Figure 2, and the final fronts are well distributed. In particular, several solutions simultaneously reduce risk and energy consumption without causing prohibitive increases in cost or service time, which confirms that the matheuristic explores non-trivial trade-off regions rather than only trivial extremes.

MILP-guided initialization plays an important role in this behavior. Instead of seeding the routing phase with entirely random truck–UAV patterns, the framework first solves small subproblems exactly and inserts these high-quality solutions into the initial population. This warm start brings realistic routing and timing structures into the search space from the beginning. It accelerates convergence, enhances the diversity of non-dominated solutions, and is particularly effective in reducing early risk violations and unnecessary energy consumption. Figure 3 shows how the average runtime per MILP-solved route increases with the number of customers. The growth is clearly non-linear. For instances larger than about 20 customers, full MILP optimization becomes computationally expensive, which supports the decision to use MILP only for small-scale seeding and local refinement. For larger instances, the heuristic routing component carries the majority of the computational burden, while MILP is applied selectively to a limited set of promising routes. This hybrid allocation of effort preserves optimization quality across all four objectives and still scales to medium and large problems.

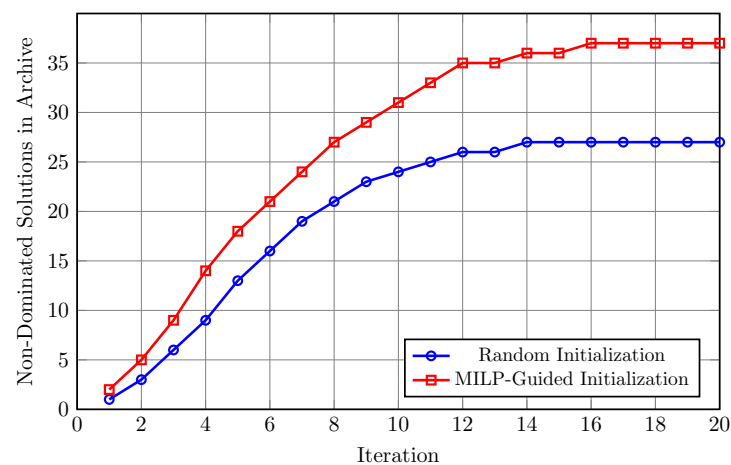


Figure 2. Growth of the Pareto archive over 20 iterations for random versus MILP-guided initialization. **Note:** MILP-guided initialization seeds the population with exact solutions from small-scale DASP subproblems, injecting structurally feasible truck–UAV routing and scheduling patterns that accelerate convergence and produce a larger, more diverse non-dominated archive than random initialization.

4.2. Pareto Front Structure and Trade-Offs

The quality of a multi-objective decision framework is reflected in the structure of its Pareto front and in how transparently it exposes trade-offs among objectives. In the proposed truck–drone delivery model, cost, delivery time, energy usage, and SO-RA-based risk must be balanced in a way that respects both operational and regulatory constraints. The first visualization (Figure 4) shows an area plot of the 40 best non-dominated solutions. Normalized values of transportation cost, delivery time, risk index, and battery usage are displayed across the solution index. The plot reveals that peaks in battery usage often coincide with higher risk levels, suggesting that faster routes, which rely heavily on UAV

sorties, tend to require more aggressive energy expenditure and may traverse higher-risk zones. The figure also shows that the least expensive solutions are not necessarily the safest. Some low-cost plans exhibit relatively high risk, which confirms that cost-only optimization is insufficient in safety-critical UAV applications.

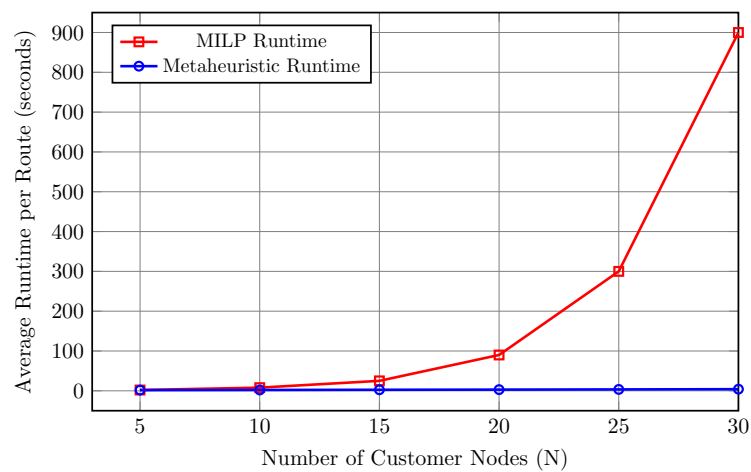


Figure 3. Average MILP runtime per route versus problem size. **Note:** Average MILP time per selected route increases nonlinearly with problem size, making full MILP optimization impractical for large instances; therefore, the hybrid framework applies MILP only to a small set of promising routes while the matheuristic performs large-scale exploration to keep runtimes tractable for tactical and daily planning.

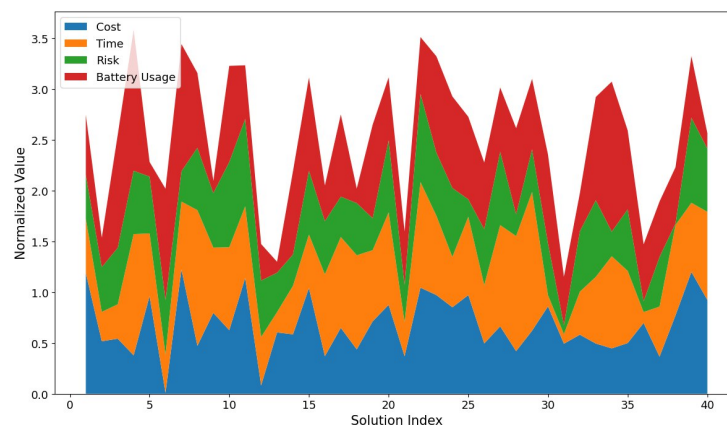


Figure 4. Area chart of normalized Cost, Time, Risk, and Battery Usage across 40 Pareto-optimal solutions. **Note:** The normalized area chart highlights trade-offs among cost, service time, operational risk, and battery usage across the Pareto set: solutions that reduce service time typically require higher battery consumption and may increase risk, underscoring the need to jointly balance cost, time, energy, and safety in truck–UAV delivery planning.

The second visualization (Figure 5) presents a correlation heatmap for the four KPIs. Battery usage exhibits a moderate positive correlation with delivery time (for example, around $r = 0.35$), but only weak correlations with cost and risk. This pattern suggests that energy constraints have a more direct impact on schedule length than on financial cost or regulatory risk. Cost and risk have an almost negligible correlation (for example, roughly $r = 0.09$), which implies that safety-related and cost-related decisions are driven by largely different factors in the optimized solutions. This decoupling is valuable in practice because it allows decision-makers to adjust safety policies without necessarily incurring a proportional cost penalty.

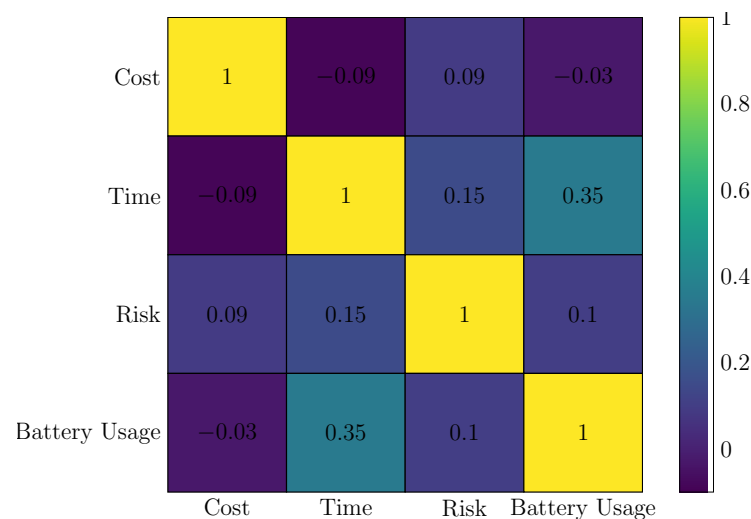


Figure 5. Correlation heatmap among the four key objectives: Cost, Time, Risk, and Battery Usage. **Note:** The correlation heatmap shows a moderate association between service time and battery usage, whereas cost and operational risk are weakly correlated, suggesting that safety-oriented decisions are not simply driven by cost minimization.

A third visualization (Figure 6) plots the Pareto front in three dimensions. Cost, time, and risk define the axes, and battery usage is encoded with color and labels. This figure shows several clusters. Solutions with low cost and low risk typically correspond to longer delivery times, while time-efficient plans tend to have higher battery usage and slightly elevated risk. The annotated battery values highlight that there are solutions with moderate energy consumption that achieve near-optimal trade-offs without extreme penalties in cost or risk. Taken together, the three figures demonstrate that the matheuristic generates a diverse and practically interpretable Pareto set, which can support various operating policies and service-level preferences.

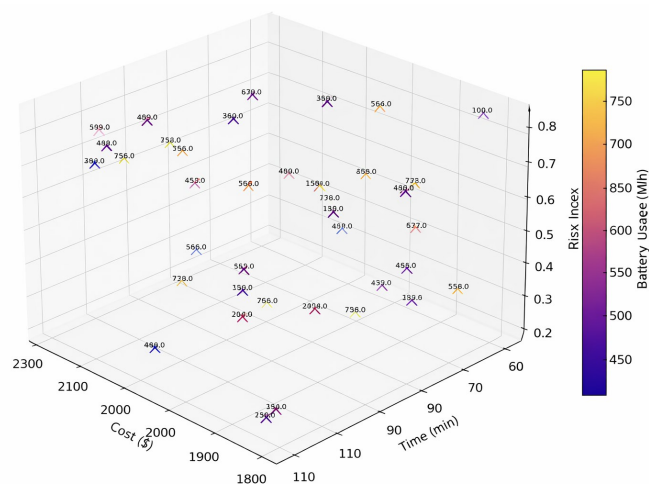


Figure 6. 3D Pareto front illustrating trade-offs among Cost, Time, and Risk, with Battery Usage annotated by color and labels. **Note:** Distinct clusters of non-dominated solutions highlight alternative operational trade-offs achievable within the proposed hybrid framework.

4.3. Structural Behavior and Scalability of the Hybrid Model

To examine the structural behavior and scalability of the proposed hybrid matheuristic, a systematic set of experiments was conducted across problem instances of increasing size and complexity. Specifically, instances with 20, 50, and 100 customers were analyzed under multiple fleet configurations and UAV operational settings. The objective of this analysis

is twofold: (i) to assess how the algorithm scales as the problem size increases, and (ii) to investigate how key system design parameters influence the relative performance of truck–drone collaboration. Four fleet configurations were considered, defined by the number of trucks ($|K|$) and the number of UAVs assigned to each truck ($|D|$) as follows:

Case 1: $|K| = 1, |D| = 1$

Case 2: $|K| = 2, |D| = 1$

Case 3: $|K| = 1, |D| = 2$

Case 4: $|K| = 2, |D| = 2$.

For each configuration, six endurance levels $\varepsilon_r \in \{0.2, 0.4, 0.6, 1.0, 1.5, 2.0\}$ and three cruising-speed coefficients $\alpha \in \{1, 2, 3\}$, which represent increasing levels of drone velocity, were evaluated. These parameters jointly control the spatial reach and temporal efficiency of UAV sorties within the hybrid delivery system. To quantify the structural benefit of UAV integration, the relative improvement of the hybrid truck–drone solution over a truck-only baseline was measured using the scalarized objective value Z , which aggregates cost, service time, energy consumption, and operational risk. The relative improvement metric Δ , defined in Equation (57), captures the percentage reduction in Z achieved by enabling UAV operations.

$$\Delta = 100 \times \frac{Z_{\text{no-drone}} - Z_{\text{with-drone}}}{Z_{\text{no-drone}}} \quad (57)$$

where Z is the scalarized objective that combines cost, time, energy, and risk.

The results, illustrated in Figure 7, reveal several consistent structural patterns. First, the proposed framework exhibits stable scalability across all tested instance sizes. Although the magnitude of Δ decreases moderately as the number of customers increases from 20 to 100, the hybrid model consistently outperforms the truck-only baseline across all configurations. This indicates that the benefits of UAV assistance are preserved even in larger and more complex delivery networks. Second, UAV endurance plays a critical role up to a threshold value. Performance gains increase significantly as ε_r grows from 0.2 to approximately 0.6, after which marginal improvements diminish. This saturation effect suggests that once most time-critical or spatially dispersed customers become reachable, further increases in endurance yield limited additional benefit. This behavior reflects realistic operational conditions, where excessively long UAV sorties are rarely exploited due to synchronization and risk constraints. Third, increases in the cruising-speed coefficient α lead to noticeable improvements in Δ , particularly for moderate endurance levels. Higher UAV speeds enable faster service of remote customers and reduce truck waiting times at launch and recovery points. However, similar to endurance, speed-related gains exhibit diminishing returns when other constraints, such as time windows, battery thresholds, or SORA-based risk limits, become binding.

Finally, fleet composition has a pronounced impact on structural performance. Configurations with two UAVs per truck consistently outperform their single-UAV counterparts, particularly in medium- and large-scale instances. The availability of multiple UAVs enables parallel sorties, enhancing temporal efficiency and reducing the need for lengthy truck detours. In contrast, increasing the number of trucks without sufficient UAV support yields smaller relative gains, highlighting the importance of balanced fleet design. Overall, this structural analysis demonstrates that the proposed hybrid matheuristic scales effectively with problem size and provides robust performance improvements under a wide range of operational conditions. The observed patterns offer practical insights for fleet configuration and UAV capability planning, supporting the use of the framework as a decision-support tool for real-world last-mile delivery systems operating under energy, time, and regulatory constraints.

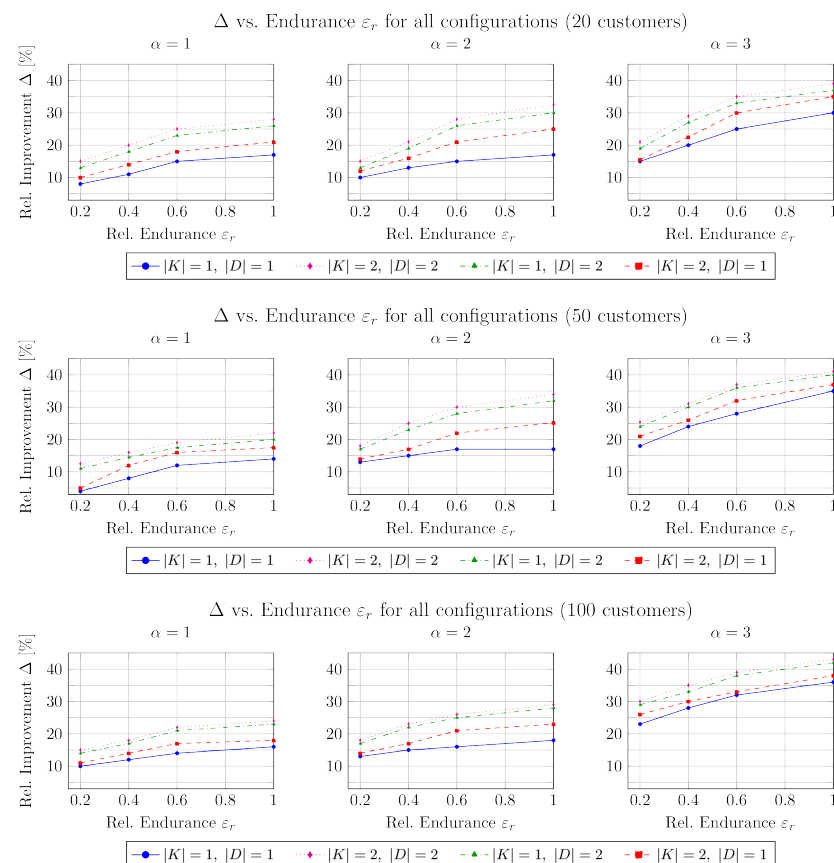


Figure 7. Relative improvement Δ versus endurance ε_r for all truck–drone configurations and $\alpha \in \{1, 2, 3\}$ under 20-, 50-, and 100-customer instances. **Note:** Relative improvement increases with UAV endurance up to a moderate level, then shows diminishing returns; configurations with two UAVs per truck consistently deliver higher gains, especially for medium and large instances, underscoring the role of balanced fleet composition.

The number of UAVs per truck also has a strong impact. Configurations with $|D| = 2$ consistently outperform their single-UAV counterparts, especially in medium- to large-scale instances where multiple parallel sorties are required to satisfy time windows and cover a larger area. In Figure 7, the performance gap between one and two UAVs per truck is visible across all α values.

4.4. Descriptive Comparison with Baseline Approaches

Although the primary focus of the performance evaluation is on the internal behavior and trade-offs of the proposed hybrid framework, a descriptive comparison with representative baseline approaches from the literature is provided to contextualize the obtained results. Compared to pure NSGA-II-based approaches commonly adopted for integrated truck–drone delivery problems, the proposed hybrid matheuristic exhibits improved Pareto front stability and coverage, particularly in terms of balancing cost, service time, energy consumption, and SORA-based operational risk. The integration of an exact MILP-based DASP in Phase 2 substantially reduces the number of infeasible or weakly dominated solutions that often arise in heuristic-only frameworks.

In comparison to decomposition-oriented matheuristics, such as that of [24], where routing and drone assignment are solved sequentially without exact refinement, the proposed approach provides more consistent coordination between truck routes and UAV operations. While the MILP refinement introduces additional computational effort, this

overhead remains acceptable for tactical and strategic planning horizons and is compensated by higher-quality and more balanced trade-off solutions.

5. Discussion

The numerical experiments demonstrate that the proposed hybrid matheuristic is capable of handling the inherent complexity of a four-objective truck-drone delivery problem while remaining computationally tractable. By combining a matheuristic routing phase with MILP-based drone assignment and scheduling, the framework systematically exploits the complementary strengths of both approaches: the matheuristic explores a wide solution space and preserves diversity, whereas the MILP subproblems enforce tight feasibility with respect to time windows, battery limits, and SORA-based risk constraints. The growth of the Pareto archive and the shape of the resulting fronts indicate that the method can uncover a rich set of non-dominated plans that substantially improve on pure-truck baselines in terms of cost, service time, and risk exposure.

The analysis of the Pareto front highlights several practically relevant patterns. First, solutions that aggressively minimize delivery time tend to rely more heavily on UAV sorties, which in turn increases both energy consumption and, in some cases, operational risk. Conversely, low-risk or low-energy solutions often accept longer completion times or higher routing costs. This reinforces the need for explicitly multi-objective planning in truck-drone systems, as no single solution dominates across all criteria. Planners must therefore select operating points that reflect regulatory constraints, service-level commitments, and sustainability targets. The weak empirical correlation between cost and risk also suggests that satisfying safety requirements cannot be treated as a simple side-effect of cost minimization, but instead requires dedicated modeling through SORA-based risk indices.

The structural experiments with different fleet sizes, endurance levels, and cruising speeds further clarify the role of system design choices in this context. Increasing the number of UAVs per truck consistently yields higher relative improvements, especially when endurance is moderate rather than extreme, reflecting a balance between sortie flexibility and diminishing returns from very long-range flights. Similarly, higher cruising speed parameters improve performance up to a point, after which gains taper as other constraints (time windows, risk scores, or battery thresholds) become binding. These patterns provide actionable insights for fleet configuration: investing in an additional UAV per truck or modest improvements in endurance may be more effective than pursuing very high-speed platforms with limited additional benefit.

From a methodological perspective, the MILP-guided warm start plays a crucial role in the framework's success. Using exact solutions from small instances to seed the routing phase accelerates convergence and steers the search toward structurally sound patterns of truck routes and UAV sorties. At the same time, restricting MILP usage to carefully selected subproblems avoids the exponential runtime growth observed when attempting to solve large instances solely by exact methods. This division of labor between exact and heuristic components explains why the framework scales well from 20 to 100 customers while still producing high-quality Pareto fronts.

5.1. Comparison with Existing Truck-Drone Delivery Studies

The obtained results are consistent with, yet extend beyond, the findings reported in prior truck-drone delivery studies summarized in Table 1. Most existing works focus on mono- or bi-objective formulations, typically optimizing cost and/or delivery time (e.g., [16,21,57]). In contrast, the proposed framework explicitly captures the trade-offs among transportation cost, service time, energy consumption, and operational risk within

a unified multi-objective optimization model. The numerical results demonstrate that solutions achieving lower operational costs are often associated with higher battery usage or increased exposure to operational risk, a trade-off that cannot be observed in cost- or time-only optimization frameworks.

From a methodological perspective, several studies listed in Table 1 rely exclusively on exact MILP formulations (e.g., [25,29]), which become computationally prohibitive as problem size increases, or on purely heuristic and metaheuristic approaches (e.g., [28,51]), which may struggle to guarantee feasibility under strict energy and safety constraints. The computational results of this study confirm that the proposed matheuristic structure effectively bridges this gap. By embedding MILP-based UAV assignment and scheduling within an NSGA-II routing framework, the model preserves solution feasibility with respect to battery endurance and regulatory risk constraints, while remaining scalable for medium- and large-scale delivery instances.

Recent multi-objective studies incorporating risk-related considerations (e.g., [40,52]) generally model risk as an abstract or aggregated metric, often detached from formal aviation safety assessment frameworks. In contrast, the SORA-based risk index adopted in this study provides a structured and regulation-aligned representation of operational risk. The resulting Pareto fronts indicate that explicitly accounting for regulatory risk reshapes the solution landscape, leading to Pareto-optimal solutions that differ substantially from those obtained under conventional risk-neutral or cost-driven formulations.

Furthermore, the structural and sensitivity analyses reveal patterns that are not reported in earlier truck–drone delivery studies. In particular, the results show that increasing UAV endurance or availability improves service time performance but may simultaneously elevate energy consumption and risk exposure, depending on fleet configuration. Such nuanced interactions among objectives are largely absent in prior studies summarized in Table 1, which typically analyze system performance under fixed fleet structures or limited objective scopes.

Overall, the comparative discussion with the existing literature highlights that the proposed framework advances the state of the art by jointly addressing four interdependent objectives, integrating a formal SORA-based risk assessment, and employing a scalable matheuristic solution strategy. These combined features explain the observed differences in solution structure and performance relative to existing truck–drone delivery models and demonstrate the added analytical value of the proposed approach for risk-aware last-mile logistics planning.

5.2. Limitations and Practical Considerations

Despite the demonstrated effectiveness of the proposed hybrid framework, several limitations should be acknowledged. First, the current formulation assumes deterministic parameters, including customer demand, travel times, and UAV energy consumption. While this assumption facilitates systematic benchmarking and structural analysis, it does not fully capture uncertainty arising from traffic congestion, weather variability, or demand fluctuations. Extending the framework toward stochastic or robust optimization formulations represents an important direction for future research. Second, the computational times reported in Figure 3 indicate that the proposed matheuristic is most suitable for tactical and daily planning applications rather than real-time operational control. Although the decomposition strategy significantly improves tractability compared to fully exact approaches, real-time re-optimization would require additional acceleration mechanisms or approximation techniques to further enhance efficiency. Finally, the assumption of one delivery per UAV sortie constitutes a deliberate modeling simplification aimed at preserving synchronization between trucks and drones and maintaining computational efficiency. While

consistent with several existing truck–drone delivery studies, this assumption may limit the benefits achievable with UAVs in dense service areas. Allowing multi-stop UAV sorties would increase operational flexibility but would also introduce additional routing, energy, and risk-coupling constraints, substantially increasing model complexity. Addressing this trade-off remains a promising avenue for future research and development. This extension is consistent with recent multi-visit and time-dependent truck–drone collaboration models (e.g., [35]), and adapting such multi-visit structures to SORA-aware risk evaluation is a promising direction for future work.

In addition, the current study focuses on synthetic benchmark instances to ensure controlled experimentation and systematic sensitivity analysis. While this choice allows for transparent evaluation of structural trade-offs and algorithmic behavior, it limits direct comparability with standard public benchmarks. Future research could adapt well-established VRP benchmark sets, such as Solomon or Christofides instances, to truck–drone delivery settings by incorporating UAV-specific constraints and risk metrics. Moreover, comparative evaluation against alternative state-of-the-art solution methods, such as adaptive large neighborhood search (ALNS), using multi-objective performance indicators (e.g., hypervolume and spacing), would further strengthen the empirical assessment. From a data perspective, applying the proposed framework to real-world urban datasets, such as e-commerce delivery logs or metropolitan regions with detailed airspace restrictions and population density data (e.g., OpenStreetMap-based layers), would enable a more realistic quantification of SORA-based operational risk. Incorporating stochastic elements related to weather conditions, demand variability, or traffic congestion, even at a simulation level, represents a natural and computationally feasible extension of the current model.

Overall, the discussion of the results indicates that the proposed matheuristic consistently delivers robust relative improvements over truck-only operations, maintains feasibility under realistic regulatory and energy constraints, and generates interpretable trade-offs among cost, time, risk, and energy. These features make the framework a practical decision-support tool for planners considering UAV-assisted last-mile delivery in urban and semi-urban environments, providing a solid foundation for the extensions and future research directions outlined in Section 6.

6. Conclusions

This paper proposed a multi-objective optimization framework for truck–drone last-mile delivery that jointly minimizes transportation cost, service time with soft time-window penalties, energy consumption, and SORA-based operational risk. The problem was formulated as a four-objective MILP and addressed through a two-phase hybrid matheuristic. In the first phase, a routing heuristic or evolutionary algorithm generates diverse truck routes and initial allocations of deliveries. In the second phase, a MILP-based Drone Assignment and Scheduling Problem refines each candidate route by optimally assigning UAV sorties while enforcing detailed temporal, capacity, battery, and risk constraints. This decomposition allows the framework to preserve modeling fidelity at the drone level while remaining scalable at the network level.

The computational study on instances with up to 100 customers demonstrated that the proposed approach can efficiently construct rich Pareto fronts, revealing the trade-offs between cost, time, risk, and energy. MILP-guided initialization was shown to accelerate convergence and improve the quality and diversity of the non-dominated archive compared with purely random seeding, while the metaheuristic component mitigates the exponential growth in runtime associated with solving large instances by exact methods alone. Sensitivity analyses over UAV endurance, cruising speed, and fleet composition revealed that moderate endurance and higher UAV availability per truck generally yield

the most attractive trade-offs, and that risk reduction does not necessarily entail a proportional increase in cost. Overall, the framework consistently delivers robust relative improvements over truck-only operations, maintains feasibility under realistic regulatory and energy constraints, and produces interpretable Pareto fronts that can support informed decision-making in practice.

From an applied perspective, the proposed model offers a flexible decision-support tool for planners considering UAV-assisted last-mile delivery in urban or semi-urban environments. The explicit representation of SORA-based risk indices, combined with cost, time, and energy objectives, enables stakeholders to explore alternative operating policies and safety levels rather than committing to a single predetermined solution. The framework can accommodate different fleet sizes, service-level targets, and regulatory assumptions, making it suitable as a basis for scenario analysis and policy design in emerging truck–drone logistics systems.

Future research can extend this work in several directions. A natural next step is to incorporate dynamic customer arrivals and stochastic elements such as travel times, traffic disruptions, and weather conditions, so that the framework supports real-time or rolling-horizon re-routing. The integration of battery degradation models, more flexible drone scheduling policies (for example, partial recharging, battery swapping, or shared UAV pools), and time-dependent energy pricing would further enrich the energy optimization layer and enable life-cycle cost analyses. From a network-design perspective, applying the model to multi-depot, cross-docking, or collaborative carrier settings could provide deeper insights into coordinated truck–drone operations at the city scale. Finally, validation through simulation on realistic road and airspace networks, or through pilot field tests, would provide valuable evidence for the practical deployment of SORA-based risk parameters, calibration, and assessment of regulatory and policy impacts.

From a methodological standpoint, future research could further enhance Pareto-front quality by integrating more advanced multi-objective optimization techniques in place of, or alongside, classical evolutionary heuristics. Recent developments in learning-assisted metaheuristics, surrogate-assisted evolutionary optimization, and hybrid exact learning frameworks offer promising directions for improving convergence speed and solution diversity in complex multi-objective logistics problems. In addition, the current DASP assumes a static representation of the airspace. An important extension would be to model the airspace as a three-dimensional grid with dynamic obstacles, such as manned aircraft or temporary airspace restrictions. In this context, graph-based path-planning methods (e.g., A* or its variants) could be used as a preprocessing step within the DASP to generate energy- and risk-aware feasible flight corridors. By assigning SORA-based risk scores as edge weights, such an approach would enable the explicit optimization of UAV trajectories under dynamic airspace conditions, while preserving compatibility with the proposed MILP-based scheduling framework.

An additional extension would involve adapting standard VRP benchmark instances (e.g., Solomon or Christofides) to drone-enabled settings and comparing the proposed framework against alternative metaheuristics using Pareto quality indicators such as hypervolume or spacing. Future work may also leverage real-world urban datasets, such as taxi-zone demand data combined with no-fly information and population density layers from OpenStreetMap, to dynamically quantify SORA-based risk under weather and demand uncertainty.

Despite the promising results, this study is subject to several limitations that should be acknowledged. First, the proposed framework assumes deterministic inputs for customer demand, travel times, and UAV energy consumption. While this assumption is common in the truck–drone delivery literature, it may limit the model's ability to fully capture

uncertainty arising from traffic congestion, weather variability, or real-time operational disruptions. Second, each UAV sortie is assumed to serve a single customer before returning to its associated truck, which simplifies the scheduling problem but may underestimate the efficiency gains achievable through multi-stop or chained drone deliveries. Third, although the SORA-based risk index provides a structured and regulation-aligned measure of operational risk, it is applied in a static manner and does not explicitly account for dynamic changes in population density or airspace usage over time. Finally, the computational experiments rely on synthetic instances, which, while suitable for methodological validation and scalability analysis, cannot fully represent the complexity of real-world urban logistics networks.

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Abbreviations

The following abbreviations are used in this manuscript:

MILP	Mixed-Integer Linear Programming
UAV	Unmanned Aerial Vehicle
SORA	Specific Operations Risk Assessment
JARUS	Joint Authorities for Rulemaking on Unmanned Systems
TDDP	Truck–Drone Delivery Problem
VRP	Vehicle Routing Problem
NSGA-II	Non-dominated Sorting Genetic Algorithm II
MOEA/D	Multi-Objective Evolutionary Algorithm based on Decomposition
DASP	Drone Assignment and Scheduling Problem
KPI	Key Performance Indicator
IP	Integer Programming
DP	Dynamic Programming
SA	Simulated Annealing
ALNS	Adaptive Large Neighborhood Search
GRASP	Greedy Randomized Adaptive Search Procedure
BBN	Bayesian Belief Network
RL	Reinforcement Learning
HGA	Hybrid Genetic Algorithm
FSTSP	Flying Sidekick Traveling Salesman Problem

Appendix A. Definitions of Variables, Sets, and Parameters

Some auxiliary variables (e.g., T_i^k , B_i^k) do not explicitly appear in the objective functions (Equations (1)–(4)) but are introduced to ensure temporal feasibility, logical consistency, and coupling between routing and assignment constraints.

Table A1. Definitions of Decision Variables.

Symbol	Decision Variables
x_{ij}^{tr}	Binary variable equal to 1 if truck $tr \in TR$ moves from node $i \in N_0$ to node $j \in N_+$ with $i \neq j$; 0 otherwise.
y_{ijB}^{tr}	Binary variable equal to 1 if the UAV of truck $tr \in TR$ departs from node $i \in N_0$, flies to $j \in N'$, and returns to the end depot or truck at node $B \in N_+$, with $\langle 0, j, B \rangle \in TP$; 0 otherwise.
SA_{ij}^{tr}	Binary variable equal to 1 if customer i is visited at any point before customer j in the route of truck tr ; 0 otherwise.
po_i^{tr}	Subtour elimination (position) variable indicating the position of node i in the route of truck tr .
t_i^{tr}	Arrival time of truck $tr \in TR$ at node i (minutes).
$t_{i tr}^{tr}$	Arrival time of the UAV associated with truck $tr \in TR$ at node $i \in \phi$ (minutes).
L_i^{tr}	Amount of load that truck tr carries at node i .
es_i	Time deviation from the earliest time allowed to provide service to demand point i in the soft time window.
ls_i	Time deviation from the latest time allowed to provide service to demand point i in the soft time window.
g_i^{tr}	Amount of battery charge of the UAV associated with truck tr at node i .
T_i^k	arrival time of drone k at node i
B_i^k	remaining battery level of UAV k after servicing node i
TWV_i^k	penalty variable representing soft time-window violation of UAV k at node i .

Table A2. Definitions of Sets.

Symbol	Sets Description
D	Set of distributor candidate locations (potential distribution facility sites).
N_0	Set of all possible departure (pickup) nodes, either truck or UAV, e.g., $N_0 = 0, 1, \dots, n, n+1, \dots, 2n$.
ϕ_k	Subset of service nodes that can be served by UAV k ; $\phi_k \subset \phi$.
ϕ	Set of all service (customer) nodes, $\phi = 1, 2, \dots, n, n+1, \dots, 2n$.
N	Set of all nodes in the network (including depots), $N = 0, 1, \dots, n, n+1, \dots, 2n+1$
N_+	Set of all possible truck arrival (delivery) nodes, $N_+ = 1, 2, \dots, n, n+1, \dots, 2n+1$.
N'	Set of all possible UAV arrival (delivery) nodes, $N' = 1, 2, \dots, n, n+1, \dots, 2n+1$.
TP	Set of UAV sortie triplets of the form $\langle i, j, k \rangle$, representing launch node i , service node j , and recovery node k (3-node UAV sorties).
F	Set of all pickup nodes, $F = 1, 2, \dots, n$.
P	Set of all delivery nodes, $P = n+1, n+2, \dots, 2n$.
$P1$	Set of delivery nodes where UAV battery recharging is available.
$P2$	Set of delivery nodes where UAV battery recharging is not available.
K	Set of UAVs.
TR	Set of trucks.
U	Set of scenarios considered in the model (e.g., for uncertainty in speed, endurance, or risk).

Table A3. Parameters Related to nodes', UAVs', or Trucks' Characteristics.

Symbol	Parameters Description
r_i	Amount of delivery demand at delivery node i.
p_i	Amount of pickup demand at delivery node i.
Q_k	Loading capacity (payload capacity) of each UAV k.
Q_{tr}	Weight (load) of truck $tr \in TR$ after visiting node i (kg).
L_j^k	Remaining load on UAV k after serving demand point j.
de_d	Center demand (or aggregated demand) associated with distributor candidate location d.
cap_d	Capacity of distributor candidate location d.
$c\bar{a}p_f$	Capacity of pickup node f.
$L0k$	Load amount on UAV k when leaving the distributor (initial payload).
d_{ij}	Distance between node i and node j.
p_u	Probability of occurrence of scenario u.
V_{ku}	Velocity of UAV k in event/scenario u.
s_{iu}	Start time of providing service to demand point i in scenario u.
V_K	Nominal speed of a UAV of type k.
n_k	Number of UAVs of type k that a single operator can operate simultaneously.
p_o	Position index of node $i \in N_+$ in the route of truck $tr \in TR$.
V_{TR}	Truck speed (miles per hour).
M_i^{TR}	Truck load capacity when serving location i with a UAV (kg).
M	A sufficiently large positive constant (big-M).

Table A4. Cost-Related Charactrestics' Parameters.

Symbol	Parameters Description
$W2$	Cost per unit time deviation from the earliest time allowed in the soft time window.
$W3$	Cost per unit time deviation from the latest time allowed in the soft time window.
fiy_k	Fixed cost of using UAV k.
C	Cost of one unit of charging energy.
CE	Cost per unit of energy.
CL	Wage (cost per unit time) of a UAV operator.
Ck	Amortized cost of UAV k.
C_k^M	Maintenance cost of a UAV of type k.
C_{ij}	Cost for truck to travel from node $i \in N_0$ to node $j \in N_+$ (\$).
C_{ij}^B	Cost to operate a UAV between nodes $i \in N_0, j \in N'$, and return to node $B \in N_+$ (\$).
C_{bat}^k	Amortized cost of the battery of UAV k.
Cp_f	Preparation cost per unit at pickup node f.
fix_d	Cost of constructing (opening) distributor candidate location d.
C_{en}	Cost associated with energy consumption.

Table A5. Battery-Related Characteristics' Parameters.

Symbol	Parameters Description
AT	Minimum amount of charging required for UAV k.
cp_{ji}	UAV battery consumption when flying from node i to node j.
$full$	Battery charging capacity (full charge level).
A_i	Amount of battery energy available on the UAV k at node i.
c_{ij}^k	Energy consumption for a UAV k to fly from location i to location j.
t_k^{bat}	Time required to replace the battery of a UAV of type k.
ch_k^0	Initial energy in the battery of a UAV of type k.
ch_k^{min}	Minimum remaining energy required in the battery of a UAV of type k.
ch_k^{max}	Maximum energy capacity of the battery for a UAV of type k.
Δch_j	Additional charge gained at charging point j.
g_i	Remaining battery energy of a UAV after returning from delivery location i.

Table A6. Risk-Related Characteristics' Parameters.

Symbol	Parameters Description
S_{ij}^k	Risk of route segment from node i to node j when traversed by UAV k.
S_{ij}^{tr}	Risk of route segment from node i to node j when traversed by truck tr.

Table A7. Time-Related Characteristics' Parameters.

Symbol	Parameters Description
S_i^{tr}	Time when truck $tr \in TR$ starts providing service at delivery node i (minutes).
S_i^k	Time when UAV k of truck $tr \in TR$ reaches node $i \in N_0 \cup N_+$ (minutes).
a_i^k	Earliest time that UAV k is allowed to provide service to distributor i in the hard time window.
b_i^k	Latest time that UAV k is allowed to provide service to distributor i in the hard time window.
ES_i^k	Earliest time UAV k is allowed to provide service to distributor i in the soft time window.
LS_i^k	Latest time UAV k is allowed to provide service to distributor i in the soft time window.
a_i^{TR}	Earliest time truck tr is allowed to provide service to distributor i in the hard time window.
b_i^{TR}	Latest time truck tr is allowed to provide service to distributor i in the hard time window.
ES_i^{TR}	Earliest time truck tr is allowed to provide service to distributor i in the soft time window.
LS_i^{TR}	Latest time truck tr is allowed to provide service to distributor i in the soft time window.
α	Scaling factor for deviations from the earliest start time in the soft time window.
β	Scaling factor for deviations from the latest start time in the soft time window.
FC_k	Time at which the route of UAV k is completed (end time of its route).
E_{iu}	Time deviation from the earliest allowed service time at demand point i in the soft time window in scenario u.
L_{iu}	Time deviation from the latest allowed service time at demand point i in the soft time window in scenario u.

Table A7. Cont.

Symbol	Parameters Description
DAY	Length of the working day (planning horizon).
l_i^k	Latest permissible time for a UAV k to provide service at location i.
l_j^k	Latest permissible time for a UAV k to provide service at delivery location j.
l_i^{tr}	Latest permissible time for truck tr to provide service at location i.
l_j^{tr}	Latest permissible time for truck tr to provide service at delivery location j.
t_{ij}	Travel time between locations i and j.
e_i	Earliest possible pickup time at location i.
τ_{ij}	Time required for truck to move from node $i \in N_0$ to node $j \in N_+$ (minutes).
τ_{ij}^k	Analogous travel time for a UAV k between nodes $i \in N_0, j \in N_+$, and return to node $B \in N_+$ (minutes).
f_i^k	Time at which a UAV k picks up the package for delivery location i at the depot.
SL_K	Time needed to load a UAV before launch (minutes).
SR_K	Time needed to recover a UAV upon rendezvous (minutes).
D^{TR}	Truck service duration at node $i \in N$ (minutes).
D^K	UAV service duration at node $j \in CN'$ (minutes).

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