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Environmental sustainability and risk-aware optimization in hybrid truck-drone logistics: A holistic multi-objective framework

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ABSTRACT

Compared to conventional truck-only systems, hybrid truck–drone delivery systems offer transformative potential for last-mile logistics by addressing operational inefficiencies, minimizing environmental impact, and enhancing safety through risk-aware optimization. This study develops a stochastic multi-objective optimization framework grounded in the Specific Operations Risk Assessment (SORA) methodology. By extending the vehicle routing problem with pickup and delivery (VRPPD) and the flying sidekick traveling salesman problem (FSTSP), the model incorporates battery optimization, CO_2 emissions reduction, and energy-efficient routing strategies. Delivery cost, time, energy consumption, operational risk, and battery performance are all optimized using a mixed-integer linear programming (MILP) and non-dominated sorting genetic algorithm II (NSGA-II) technique. Sensitivity analysis show that increasing drone fleet size and efficiency results in significant cost, time, and energy savings while improving safety. The model's flexibility in both urban and remote delivery contexts is confirmed by numerical trials. In line with life cycle analysis (LCA), this study offers practical advice for environmentally responsible and risk-aware logistics, assisting decision-makers and industry participants in the development of scalable and sustainable solutions.

1. Introduction

1.1. Background and motivation

Unmanned Aerial Vehicle (UAV)-assisted delivery systems have drawn a lot of interest recently from businesses and governments around the world, not only as a way to improve operational efficiency but also as a promising way to improve environmental sustainability by lowering emissions and energy use. Drones have been used by Chinese companies like Zipline and JD.com to transport goods to far-flung areas (Purtell et al., 2025; Mulvey et al., 1995; Shen and Sun, 2023), demonstrating the drones' potential to lower the carbon footprint of logistics operations. Furthermore, in December 2013, Amazon started experimenting with UAV package delivery (Ponza, 2016). Since then, drone deliveries have emerged as a viable option for a number of creative companies. Other well-known UAV projects include Google's Project Wing and DHL's Parcelcopter, in addition to Amazon's Prime Air UAV. In October 2019, the Federal Aviation Authority (FAA) allowed UPS the approval to operate a drone airline, allowing UPS drones to fly beyond the operator's line of sight, over populated areas, and during nighttime. In Europe, the Single European Sky ATM Research (SESAR) program, authorized by the European Union, has been investigating the integration of drones into European airspace for applications such as parcel delivery (Doole et al., 2020; Purtell et al., 2024). These developments highlight the increasing global interest in UAV-based delivery systems and underscore the necessity to develop adaptable models and methods suitable for diverse geographic and regulatory environments. However, the limited battery life of drones presents a significant challenge to their widespread adoption, particularly in urban logistics. Addressing this limitation requires models that not only optimize operational efficiency but also minimize battery consumption to ensure the environmental benefits of UAV systems are fully realized.

This research introduces a transformative integrated delivery framework that enhances operational flexibility while addressing last-mile inefficiencies. Our proposed system strategically integrates risk minimization with sustainability objectives, bridging the gap between

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safe operations and environmental stewardship. By employing SORA approach and optimizing energy consumption, the model ensures both safety and sustainability in diverse logistics scenarios (X. Zhang et al., 2022; Matalonga et al., 2024). Such advancements are essential as standalone UAV delivery systems encounter significant challenges. For example, the research by Sajid et al. adapted benchmark instances from the capacitated vehicle routing problem (CVRP) to fit the constraints of UAV delivery systems. Their operational range is constrained by factors including maximum cargo capacity and limited battery life, which make it impossible to accurately simulate real-world situations (Sajid et al., 2022). UAVs and trucks can, however, complement one other well. UAVs can deliver lighter, smaller cargo faster, while vehicles can move larger, bulkier items despite their slower pace. As a result, trucks may be able to operate farther than UAVs.

More complex decision-support systems in UAV-based logistics are now possible thanks to recent developments in optimization techniques. Research like Mahmoodi et al. (2022a,b) showed how effective it is to combine precise and metaheuristic techniques in order to reduce response times in dynamic disaster management situations. Similarly, Mahmoodi et al. (2025) strengthened the potential of hybrid optimization in real-time aerial logistics by combining Bayesian belief networks with NSGA-II to improve UAV delivery efficiency under uncertainty. The transition to intelligent, risk-informed delivery frameworks that adapt dynamically to changing demand and environmental conditions is best illustrated by these works. Additionally, game-theoretic models have been used to maximize supply chain coordination in complicated networks (Narenji et al., 2025), establishing the foundation for last-mile delivery systems that involve multi-agent collaboration.

From a broader perspective, the development of robust, stochastic, and simulation-based models has significantly contributed to the logistics and operations research domains. Multi-objective models for situations with high levels of uncertainty and machine failures were developed by Aiassi et al. (2020) and Sajadi et al. (2019). These models provide insights that are directly relevant to the deployment of UAVs in restricted urban airspaces. The argument for integrating flexibility and sustainability in logistics is further supported by simulation-based NSGA-II methodologies (Amelian et al., 2022) and robust supply chain optimization strategies (Rabbani et al., 2022). Green delivery scheduling and environmental risk mitigation are the focus of recent studies by Ganji et al. (2021), Shahbazi et al. (2017), and Rabet et al. (2024), which support the incorporation of energy and CO_2-related objectives. Furthermore, the use of soft computing in aviation risk analysis (Nosrati Malekjahan et al., 2025) and the incorporation of analytics-driven decision frameworks into supply chains (Kakhki and Sajadi, 2024) demonstrate the increasing importance of data-driven, risk-aware strategies in the future of UAV-based logistics.

This research broadens the scope to include globally flexible truck-drone delivery frameworks, whereas previous models have mostly concentrated on region-specific implementations. The suggested approach adapts to various infrastructure constraints and regulatory circumstances by taking into account a variety of operating contexts, such as urban, suburban, and distant settings. Murray and Chu (2015), for instance, looked at truck-UAV coordination, although their model was only applicable to organized cities with clearly defined airways and delivery routes. In contrast, our approach is designed to function across heterogeneous terrains, supporting flexible deployment under a broad spectrum of logistical scenarios. These existing limitations and fragmented approaches highlight the need for models that holistically integrate safety, environmental performance, and operational efficiency in hybrid truck–drone delivery systems.

1.2. *Scientific motivation for risk- and sustainability-based optimization*

A central scientific motivation for this study is the lack of integrated risk-aware and sustainability-oriented optimization frameworks in hybrid truck–drone logistics. Existing UAV-based delivery models largely focus on cost, travel time, or payload constraints, while overlooking two critical dimensions that fundamentally determine real-world feasibility: operational risk and environmental performance. From a risk perspective, UAV operations are highly constrained by aviation safety regulations such as SORA, where risk levels directly dictate allowable flight corridors, operational mitigations, and the feasibility of BVLOS missions. Current optimization models typically treat safety as an external regulatory limitation rather than a quantitative decision variable. Transforming SORA-based safety considerations into a formal optimization objective fills a major scientific gap by enabling risk-informed routing decisions that adapt to airspace density, ground population distribution, and failure probabilities.

Similarly, sustainability has emerged as a core challenge in modern logistics, yet most routing models treat energy consumption and emissions as secondary outputs. The limited battery capacity of UAVs, combined with global decarbonization targets, necessitates models that explicitly optimize battery usage, energy efficiency, and CO_2 emissions. Integrating these metrics directly into the objective function advances the literature by establishing a multi-objective, environmentally conscious decision framework aligned with life-cycle assessment principles and sustainable logistics strategies. By addressing these two gaps, this research provides a unified hybrid truck–drone model that captures the real constraints of regulatory safety requirements and environmental performance, thereby contributing a scientifically grounded framework for next-generation aerial-ground delivery systems.

1.3. *Contribution and model overview*

Building on this foundation, we introduce a novel multi-objective hybrid optimization model that integrates MILP and NSGA-II within a risk-aware planning framework guided by SORA. Unlike classical hub-and-spoke systems with fixed infrastructure and deterministic flows, the truck–drone system modeled in this study requires dynamic launch and retrieval coordination, battery-driven flight feasibility, and risk-aware aerial routing, resulting in a fundamentally different optimization structure. In this framework, the truck operates as a mobile micro-hub whose location and timing are endogenously determined within the optimization process, an architectural feature that does not exist in traditional hub-and-spoke formulations. The model simultaneously optimizes cost, delivery time, risk exposure, and battery consumption, while adhering to operational constraints such as soft time windows (Yang et al., 2023), energy thresholds, and infrastructure access.

It supports dynamic route planning over long distances and for mixed payloads, offering enhanced efficiency and resilience in various delivery environments. Table 1 provides a comparative overview of recent optimization-based UAV logistics models. The remainder of this paper is structured as follows: Section 2 outlines the system design and problem framework; Section 3 presents the mathematical formulation and integration of SORA; Section 4 details the NSGA-II solution procedure; Section 5 discusses simulation results and sensitivity analyses; and Section 6 concludes with managerial implications and directions for future research. By explicitly treating risk and sustainability as core optimization objectives rather than external regulatory or environmental constraints, this study advances a new class of risk-aware, environmentally informed hybrid truck–drone delivery models, addressing well-documented gaps in the contemporary UAV logistics literature.

A comprehensive review of the existing research highlights how the current study fills gaps identified in previous works. This research focuses on a well-established pickup and delivery problem (PDP), as developed in Mahmoodi et al.'s (2024) foundational study. The enhanced model presented here incorporates time window constraints, simultaneous pickup and delivery demands, and rechargeable battery features, all of which are essential for managing remotely piloted aircraft system (UAVs) networks. The model is designed for scenarios where each vehicle, starting from a central depot, picks up items from

Table 1
Comparison of optimization methods and criteria for UAV-Based logistics models (Bi et al., 2024a, 2024b; Mulumba and Diabat, 2024; Eskandaripour and Boldsaikhan, 2023; Kumbhar and Shin, 2022; Arishi et al., 2022; Guo et al., 2023; Jiao et al., 2022; Kyriakakis et al., 2023; Sham et al., 2023; Bhuiyan et al., 2022; Hashemi et al., 2022; Nguyen et al., 2022; Mahmoodi et al., 2022; Millar et al., 2023; Dell'Amico et al., 2022; Vu et al., 2022; Liu et al., 2022; Gohari et al., 2022; Chang and Laliberté, 2023; Wu et al., 2022; Kong et al., 2022; Nguyen et al., 2022; Sham et al., 2023; Zhang et al., 2022; Yu et al., 2022; Yang et al., 2023; Freitas et al., 2022; Sajadi et al., 2019).

Author(s)	Optimization Methods	Hybridization		Datasets		Objective Functions			Criteria for Optimization																	
									Costing		Non-Costing															
															Time			Risk Assessment								
		Truck-Drone Delivery	Drone Delivery	Benchmark	Real World	Reference Point	Weight Sum	Pareto Dominance	Operating Cost	Non-Operating Cost	Room stability	Room capacity	Workload Capacity	Working days	Time Windows	Idle Time	Consecutive Periods	AHP	BBN	SORA Standard	Battery Consumption	Perturbation	Travel distance	Room facilities	Robustness	LCA
Bi et al., 2024	Multi-Agent Reinforcement Learning	✓		✓				✓	✓			✓		✓		✓					✓				✓	✓
Mulumba and Diabat, 2024	Metaheuristic Optimization Algorithms		✓		✓			✓		✓	✓			✓		✓							✓		✓	
Eskandaripour and Boldsaikhan, 2024	Metaheuristic Optimization Algorithms		✓	✓		✓			✓				✓				✓						✓		✓	✓
Kumbhar et al., 2022	Machine Learning	✓		✓		✓		✓	✓			✓		✓		✓					✓				✓	✓
Arishi et al., 2022	Machine Learning	✓		✓		✓		✓	✓			✓	✓		✓						✓	✓			✓	
Guo et al. 2023	Reinforcement Learning		✓		✓			✓		✓	✓			✓		✓							✓		✓	
Jiao et al., 2023	Dynamic Model		✓				✓			✓					✓					✓					✓	✓
Kyriakakis et al., 2023	GRASP/VND algorithm		✓		✓			✓	✓				✓	✓			✓						✓		✓	
Sham et al., 2023	Metaheuristic Optimization Algorithms		✓		✓		✓		✓			✓				✓						✓		✓	✓	
Bhuiyan et al., 2022	Metaheuristic Optimization Algorithms		✓		✓			✓							✓						✓	✓			✓	
Hashemi et al, 2022	Meta-Heuristic Algorithms		✓	✓				✓	✓					✓	✓			✓		✓			✓		✓	✓
Nguyen et al, 2022	Meta-Heuristic Algorithms	✓		✓		✓		✓	✓			✓		✓		✓					✓				✓	
Mahmoodi et al., 2022	Robust Optimization Model		✓	✓				✓		✓					✓			✓		✓			✓		✓	✓
Millar et al., 2023	Reinforcement Learning Algorithm		✓	✓				✓	✓				✓			✓			✓	✓					✓	
Dell'Amico et al., 2022	Meta-Heuristic Algorithms				✓	✓				✓	✓	✓				✓						✓	✓	✓		✓
Vu et al., 2022	Meta-Heuristic Algorithms	✓		✓				✓	✓				✓	✓		✓	✓									✓
Liu et al., 2022	Reinforcement Learning		✓		✓		✓			✓	✓			✓	✓								✓		✓	
Gohari et al., 2022	Meta-Heuristic Algorithms		✓	✓				✓	✓			✓			✓		✓	✓		✓			✓		✓	✓
Chang and Laliberte, 2023	Meta-Heuristic Algorithms		✓	✓				✓		✓			✓	✓			✓					✓	✓		✓	
Wu et al., 2022	Meta-Heuristic Algorithms	✓			✓		✓		✓				✓	✓		✓	✓									✓
Kong et al., 2022	Meta-Heuristic Algorithms		✓	✓				✓	✓			✓			✓		✓	✓		✓			✓		✓	
Nguyen et al, 2023	Metaheuristic Optimization Algorithms		✓		✓			✓		✓		✓			✓						✓	✓			✓	
Shen et al., 2023	Meta-Heuristic Algorithms		✓		✓			✓	✓				✓	✓			✓					✓	✓		✓	
Zhang et al., 2022	Machine Learning	✓		✓				✓	✓				✓	✓		✓	✓							✓		✓
Yu et al., 2022	Meta-Heuristic Algorithms	✓		✓				✓	✓			✓		✓	✓		✓					✓	✓	✓		
Yang et al., 2023	Multi-Agent Reinforcement Learning		✓	✓				✓	✓				✓			✓			✓	✓			✓		✓	
Freitas et al., 2022	Exact And Heuristic Approaches	✓		✓		✓			✓			✓		✓	✓		✓					✓	✓	✓		
Sajid et al., 2022	Metaheuristic Optimization Algorithms		✓		✓			✓							✓						✓	✓			✓	✓
Bi et al., 2023	Deep Reinforcement Learning	✓		✓				✓	✓				✓	✓		✓	✓				✓		✓			✓
Our article	Meta-Heuristic Algorithms	✓		✓				✓	✓	✓			✓	✓	✓		✓		✓	✓	✓		✓			✓

one location and delivers them to another, with the objective of minimizing operational costs. For instance, in a delivery service required to visit several customers, some items need to be picked up before being delivered. Fig. 1(a) illustrates this scenario, while Fig. 1(b) shows a potential solution to this pickup and delivery problem.

This study expands on the existing model with the following enhancements:

1. Optimization of Key Performance Indices: The model is initially designed to address several crucial performance indices essential for optimizing logistics operations. The primary goal is to minimize operational costs by strategically routing trucks and drones, leveraging their respective advantages in terms of cost and time. This is modeled through a MILP. Due to safety concerns, especially with the introduction of new technologies, drones are restricted to delivery tasks only, with package pickups managed exclusively by trucks. Furthermore, truck drivers are responsible for deploying and retrieving drones, ensuring that business efficiencies and safety are prioritized over simple route optimization. Further details on this MILP can be found in Section 3.2.
2. Robust Optimization Framework: The model is enhanced with a robust optimization framework that minimizes delivery times through scenario-based planning, taking into account varying factors such as traffic and weather conditions within predefined time windows.
3. Risk Minimization and SORA Compliance: It incorporates risk minimization strategies that comply with SORA approach, ensuring safe UAV operations in complex urban environments and regulated airspaces. Moreover, the model introduces innovations in energy optimization by carefully managing drone battery consumption, which is particularly important given the limited endurance of current UAV technologies.
4. Dual Focus on Complexity and Practicality: The model stands out due to its dual focus on high operational complexity and practical applicability, directly addressing challenges faced by major logistics companies like Amazon, DHL, and FedEx. It integrates multi-scenario delivery options and complex algorithmic solutions, advancing the practical application of drone-assisted delivery systems in both North America and Europe. This approach is not purely theoretical; it is designed to meet the real-world demands of large-scale logistics operations, providing adaptable, efficient, and risk-managed delivery systems. By incorporating multi-objective location-routing problems and leveraging advanced risk assessment methodologies, such as SORA, the framework aims to set a new benchmark in logistics, offering viable solutions for a range of geographical and regulatory environments.
5. Optimization Using NSGA-II: The model employs the NSGA-II to solve the optimization problem. This allows for an efficient trade-off analysis between conflicting objectives, such as cost, time, risk, and energy consumption. The study not only contributes to academic research but also provides actionable frameworks for businesses

seeking to improve their logistical operations through cutting-edge technologies.

The paper is structured as follows: Section 2 outlines the framework for the drone-assisted pickup and delivery problem, emphasizing its alignment with sustainability goals. In Section 3, the model is optimized using the NSGA-II algorithm, focusing on trade-offs between environmental and operational objectives. Section 4 presents results highlighting significant reductions in CO2 emissions and energy consumption, and Section 5 concludes with implications for sustainable logistics.

2. Integrated system configuration and operational design

This section provides an in-depth overview of the structural and operational design of the proposed hybrid UAV–truck delivery model. It outlines the architecture of the integrated system, describing the routing framework, vehicle coordination, and sustainability-oriented features. The model's key components such as depot positioning, battery-aware routing, and the application of renewable energy sources are detailed to illustrate how environmental and logistical objectives are simultaneously addressed. The subsequent subsections present the problem description and mathematical formulation supporting the model.

2.1. Problem description

Building on recent advancements, this study contributes to the existing literature by addressing the pickup and delivery problem within the context of drone-assisted logistics. The proposed model and solution methodology extend the FSTSP framework, utilizing the latest solution techniques to comprehensively optimize drone-assisted pickup and delivery operations. A key innovation of this study is its focus on environmental sustainability by minimizing energy consumption and optimizing battery usage, which directly reduces the carbon footprint of logistics operations. Additionally, the model integrates risk minimization strategies, aligning with SORA approach to ensure safe and sustainable UAV operations.

The model incorporates a closed-loop route with several key elements, including a central depot, pickup points, drop-off points, and combined pickup and drop-off locations. Fig. 2 depicts an integrated logistics system where both trucks and drones are utilized for package delivery. The central depot serves as the starting point for both vehicles. Trucks follow specific routes, stopping at designated pickup (green triangles) and drop-off points (black triangles), which act as intermediate nodes for collecting or delivering packages. Drones complement the trucks by providing rapid and flexible transportation between these points. As shown, drones take off and land at various demand points (blue spheres) along the route, facilitating dynamic coordination with the trucks. Red arrows represent the flight paths of the drones, while grey roadways indicate the trucks' routes. The drones primarily handle short-distance deliveries from the trucks to final destinations or between pickup points, increasing the overall efficiency and reach of the delivery network. A key feature of this model is its ability to optimize energy usage by accounting for drone battery limitations and charging requirements. The model integrates the use of renewable energy sources for drone charging, promoting sustainability throughout the system's lifecycle. This consideration aligns with the LCA approach, ensuring that the environmental benefits extend beyond operational phases to include production and disposal processes. Although a full LCA covering manufacturing, maintenance, and disposal is beyond the scope of this study, our framework captures the use-phase environmental impact of truck–drone delivery operations. By quantifying operational energy consumption and CO_2 emissions, we align with the LCA perspective on emissions in the active phase of the logistics life cycle.

The combination of trucks and drones enhances the logistics system, ensuring prompt deliveries, particularly in regions with difficult terrain or limited road infrastructure. This synergy maximizes operational efficiency while addressing logistical challenges in diverse environments. Moreover, by incorporating dynamic coordination and real-time adjustments, the model achieves a balance between environmental goals and operational demands. This approach highlights the potential for truck-drone systems to align with broader sustainability objectives, making them a viable solution for policymakers and businesses aiming to reduce environmental impacts while maintaining high levels of service efficiency.

The model encompasses three distinct operational scenarios, each designed to optimize energy consumption, reduce environmental impact, and ensure safety in UAV-truck operations:

- **Scenario A:** In this scenario, the UAV is entirely dependent on the truck and cannot operate independently. The UAV departs from the depot, visits two designated green nodes, and must return to the depot without separating from the truck. The dashed lines illustrate that the UAV's movements are directly tied to the truck's route, highlighting its operational limitation in functioning autonomously. This scenario minimizes battery consumption by reducing the UAV's operational range, aligning with sustainability goals while ensuring safety through close coordination with the truck.

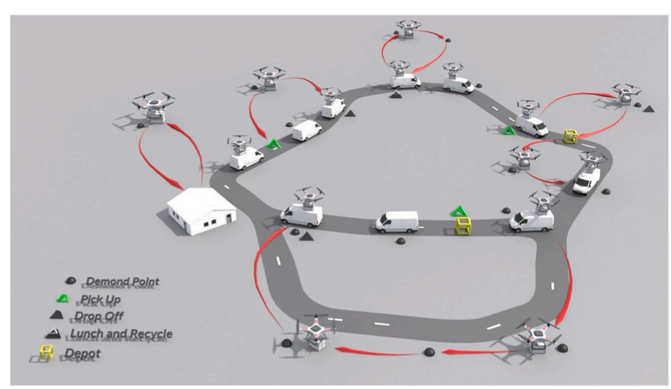
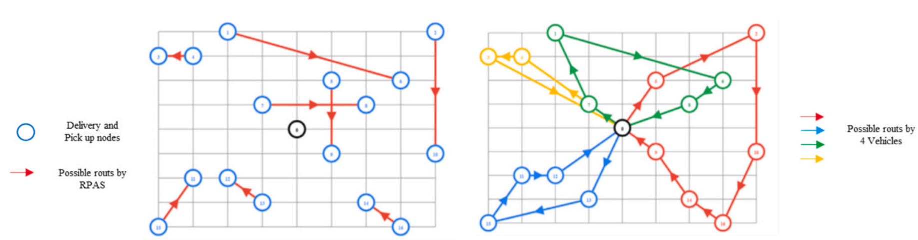


Fig. 2. Schematic view of the integrated drone and truck-based optimization model for UAVs logistics and delivery system.



(a) (b)

Fig. 1. The pickup and delivery problem. (a): Directed edge from pickup to delivery. (b): Vehicle routes. Source: OR.Tools (2019).

- **Scenario B:** This scenario presents a situation where a new UAV sortie cannot be initiated until the UAV has been retrieved after completing its previous mission. The UAV first visits a green node, then returns to the truck before it can continue to the next green node. This sequence ensures that the UAV must rendezvous with the truck before performing any subsequent tasks. By limiting the UAV's flight to manageable distances, this scenario reduces energy consumption and allows for the integration of renewable energy sources for UAV charging, enhancing the system's environmental sustainability.
- **Scenario C:** In this case, the UAV's launch and rendezvous points must differ. After departing from the depot and visiting a green node, the UAV cannot return to its starting point; instead, it must rendezvous with the truck at a new location further along the truck's route. This scenario underscores the importance of detailed logistical planning to optimize both the UAV's route and the overall operational efficiency. It allows for more flexible energy management strategies and is particularly effective in reducing the system's overall carbon footprint by minimizing redundant travel paths.

Fig. 2 illustrates the system's network design. Since the coordination between the UAV and the truck originates from a central depot, each scenario imposes different constraints on UAV operations. These scenarios introduce various operational restrictions aimed at enhancing both the safety and efficiency of the integrated UAV-truck delivery system while addressing broader sustainability objectives. By aligning with SORA approach, the model ensures safe deployment of UAVs in complex logistical networks. Furthermore, the scenarios contribute to a LCA of energy consumption, providing valuable insights for policymakers seeking to implement sustainable and efficient logistics frameworks.

Table 2 offers a thorough overview of the important parameters, assumed value ranges, and the sources or justifications that go along with them to improve the model's realism and reproducibility. These include drone efficiency (60–100 %), battery capacity (100–250 Wh), and the number of delivery vehicles (10–50), all of which are measured against empirical specifications from Sajadi et al. (2019) and Ganji et al. (2021). To represent typical urban/suburban ranges, the average delivery distance was chosen between 5 and 15 km. Energy consumption values (12–18 Wh/km) were derived from UAV energy usage data, while the risk index values (scaled 0–100) were scenario-generated based on SORA classifications, ensuring consistency with aviation safety standards. Operational cost (0.25–0.60 $/km) and delivery time (0.01–0.025 h) reflect hybrid fleet benchmarks and are refined based on the NSGA-II optimization outputs. CO_2 emissions (0.5–1.5 kg per trip) were estimated from fuel and electricity conversion factors. This parameter table strengthens model transparency and external validity by clarifying scenario calibration and input derivation strategies. The impact of varying key inputs, including drone efficiency and vehicle fleet size, was examined to test the robustness of the results under different operational conditions.

2.2. Problem formulation

In this section, the model builds upon the MILP framework presented by Mahmoodi et al. (2024) to incorporate UAV deliveries into routing problems. Specifically, the model addresses a set of pickup requests, where each request iii is associated with an origin node i and a destination node n + i. The trucks and UAVs are assumed to operate from a single central depot, represented as nodes 0 (departure) and 2n+1 (return). The drone-assisted pickup and delivery problem (DAPDP) is modeled using a directed graph G= (N, U), where N represents the set of nodes (customer locations), and U denotes the directed arcs corresponding to different routing scenarios within the graph.

2.2.1. Mathematical model

2.2.1.1. Objective 1: Minimization of total operational cost (Z1). The goal of this function is to minimize the overall operational costs, including transportation costs for trucks and UAVs, charging costs, and fixed costs for facilities.

$$Z_1 = min\sum_{i\in N_0}\sum_{j\in N_+}\left(C_{ij}^T.X_{ij}^T + C_{ij}^U.Y_{ij}^U + C_{ij}^{UT}.Z_{ij}^{UT}\right) + \sum_{u\epsilon U} Fc_U.\, Z_U + W_1.P^T\sum_{j\in N_+}\left(La_j^T\right) + W_2.P^U.\sum_{j\in N_+}\left(La_j^U\right) \tag{1}$$

Where:

- Z_U is a binary decision variable that takes the value 1 if facility k is selected, and 0 otherwise.
- Z_{ij}^{UT} is the binary decision variable indicating if both truck and UAV serve the same route i→j.
- C_{ij}^T and C_{ij}^U are transportation costs for trucks and UAVs on route i→j, respectively.
- C_{ij}^{UT} represents the combined cost when both truck and UAV are selected to serve node i→j
- Fc_U is the fixed cost for operating facility k.
- P^T and P^U represent penalties for deliveries outside the soft time window.
- W_1 and W_2 are penalty weights for trucks and UAVs.
- La_j^U *and* La_j^T indicates the lateness penalty for node j.

2.2.1.2. Objective 2: Minimization of total service time (Z2). This objective minimizes the total service time for both trucks and UAVs by considering the different velocities and possible delays caused by air traffic and road conditions.

$$Z_2 = min\sum_{i,j\in N_0}\sum_{u\epsilon U}\left(At_{ij}^T.X_{ij}^T + At_{ij}^U\, Y_{ij}^U + At_{ij}^{TU}\, Z_{ij}^{UT}\right) \tag{2}$$

Where:

At_{ij}^T and At_{ij}^{UAV} are the service times for trucks and UAVs on route i→j, respectively.

At_{ij}^{TU} is the minimum time when both truck and UAV are used, i.e., the fastest mode between the two.

2.2.1.3. Objective 3: Minimization of risk index (Z3). This function reduces the total risk associated with each route, considering both ground

Table 2
Summary of model parameters, assumptions, and data sources.

Parameter	Assumed Value/ Range	Source/Justification
Number of Delivery Vehicles	10–50	Calibrated based on Mahmoodi et al. (2025)
Drone Efficiency (%)	60–100	Scenario-based; benchmarked with Ganji et al. (2021)
Battery Capacity (Wh)	100–250	Typical drone specs in Sajadi et al. (2019)
Average Delivery Distance (km)	5–15	Urban/suburban range – estimated
Energy Consumption per km (Wh/km)	12–18	Derived from UAV energy use data
Risk Index (scaled 0–100)	30–80	Scenario generation based on SORA risk levels
Operational Cost per km ($)	0.25–0.60	Operational benchmark for hybrid fleets
Delivery Time per Trip (hr)	0.01–0.025	Based on NSGA-II optimization results
CO2 Emissions (kg per trip)	0.5–1.5	Estimated from fuel/electricity usage

and air risks for trucks and UAVs. Ground risks include risks to third parties on the ground, while air risks account for air traffic and weather conditions.

$$Z_3 = min\sum_{i\in N_0}\sum_{j\in N_+}\left(R^T_{ij}.X^T_{ij} + R^U_{ij}Y^U_{ij} + R^{TU}_{ij}.Z^{UT}_{ij}\right) \tag{3}$$

Where:

- R^T_{ij} and R^U_{ij} represent the risk indices for trucks and UAVs on route i→j, respectively.
- R^{TU}_{ij} represents the **combined risk** when both truck and UAV serve the same route i→j.

Drone efficiency in this study refers to the ratio of effective delivery output (i.e., payload and range) to total energy consumed, expressed as a percentage. A higher efficiency implies faster delivery, reduced emissions, and optimized battery usage.

2.2.1.4. Objective 4: Minimization of battery consumption (Z4)

$$Z_4 = min\sum_{i\in N_0}\sum_{j\in N_+}\left(Bu^U_{ij}.\ Y^U_{ij} + Bu^{TU}_{ij}.Z^{UT}_{ij}\right) \tag{4}$$

Where:

- Bu^U_{ij} is the battery consumption for UAVs on route i→j.

Subject to:

$$\sum_{B\in N_+}\sum_{j\in C}\sum_{i\in N_0} y^{TU}_{ij} \geq 1 - \sum_{B\in N_+}\sum_{j\in C}\sum_{i\in N_0} x^{TU}_{ij} \tag{5}$$

$$\sum_{ij\in N_0\cup C} y^{TU}_{ij} = \sum_{ij\in N_0\cup C} y^{TU}_{ijB} \tag{6}$$

$$S_i + \frac{d\left(y^{TU}_{ij} + x^T_{ij}\right)}{V_{tru}} - M.\left(1 - y^{TU}_{ij}\right) \leq S_j \tag{7}$$

$$S_i + \frac{d\left(y^{TU}_{ij} + x^T_{ij}\right)}{V_{tru}} + M.\left(1 - y^{TU}_{ij}\right) \geq S_j \tag{8}$$

$$\mathrm{E_i} \geq \alpha\ (\mathrm{ES_i} - \mathrm{S_i}) \tag{9}$$

$$L_i \geq \beta\ (S_i - LS_i) \tag{10}$$

$$\mathrm{A_i} = \mathrm{full} \tag{11}$$

$$\mathrm{A_i} \leq A_j - \left(y^{TU}_{ij}.FC_U + M.\left(1 - y^{TU}_{ij}\right)\right) \tag{12}$$

$$\mathrm{A}^U_{\mathrm{i}} \geq \mathrm{AT} \tag{13}$$

$$Z_d.M \geq \sum_{U\in R}\sum_{i\in P\cup N_+} y^{TU}_{ij} \tag{14}$$

$$\mathrm{T}_U \geq \mathrm{S_i} + \frac{\mathrm{d}y^U_{ij}}{\mathrm{V}_U} + \frac{dx^T_{ij}}{\mathrm{V}_T} - \mathrm{M}.\left(1 - y^{TU}_{ij}\right) \tag{15}$$

$$\sum_{k\in K}\sum_{i\in C}\sum_{j\in P} S^U_i \times y^{TU}_{ij} + \sum_{k\in K}\sum_{i\in P\cup N_+}\sum_{j\in P} S^T_i \times x^T_{ij} \leq DAY \tag{16}$$

$$y^{TU}_{ij}, Z_d, Y_{df} = 0\ or\ 1 \tag{17}$$

$$L_j, S_i \geq 0 \tag{18}$$

$$s^{\mathrm{U}}_{ij} \leq \mathrm{M}\sum_{i\in C} y^{TU}_{ij} \tag{19}$$

$$s^{\mathrm{U}}_{ij} \leq \mathrm{M}\sum_{i\in C} x^T_{ij} \tag{20}$$

$$\sum_{i\in C} c^U_{ij} z_{ij} \leq \left(ch^0_U - ch^{min}_U\right) \tag{21}$$

$$M_j \sum_{i\in C} z_{ij} \leq M^{max}_U \tag{22}$$

$$f_j \geq f_i + (t_l + t_{ij} + t_u) + t^{bat}_U y_i - M(1 - z_{ij}) \tag{23}$$

$$S^U_i \geq S^T_i + \tau_{hU} + D^T_h + SL_U\left[\sum_{i\in N_0}\sum_{j\in N_+} y^{TU}_{ij}\right] + SR_U\left[\sum_{i\in N_0}\sum_{j\in N_+} y^{TU}_{ij}\right], \tag{24}$$

$$S^U_j \geq S^U_i - M\left[1 - \sum_{i\in N_+} y^{TU}_{ij}\right] \tag{25}$$

$$S^U_B \geq S^U_j + D^U_j - M\left[1 - \sum_{i\in N_0} y^{TU}_{ij}\right] \tag{26}$$

$$ch^0_U - \sum_{i,j\in P} c^U_{ij} x^U_{ij} + \sum_{j\in D_2} \Delta ch_j \leq ch^{max}_U \tag{27}$$

$$g_j \leq ch^0_k - \sum_{i,j\in P} c^U_{ij}.x^U_{ij} \tag{28}$$

$$g^t_i \geq -ch^{min}_U \tag{29}$$

$$c^U_{ij}\ x_{Ui} \leq \left(ch^0_U - ch^{min}_U\right) \tag{30}$$

The constraints in the model serve various purposes to optimize the UAV logistics system, with a particular focus on sustainability, risk management, and operational efficiency. Constraints (5) and (6) focus on UAV allocation and route efficiency: Constraint (5) allows flexible allocation of UAVs and trucks to service delivery nodes, while Constraint (6) mandates that specific points must be served. These constraints ensure balanced resource allocation while minimizing unnecessary energy consumption, directly supporting sustainability objectives. Constraints (7) and (8) manage time and capacity by determining service start times, ensuring efficient utilization of both UAVs and trucks. Constraints (9) and (10) handle time window and battery management, allowing for deviations from soft time windows while optimizing energy use. Constraint (11) requires full charging at designated points using renewable energy sources, and Constraint (12) calculates the remaining battery capacity to minimize wastage. Constraint (13) enforces battery limitations, aligning with LCA principles to reduce the system's environmental impact over its operational lifespan.

Constraint (14) deals with the construction of distribution centers (DCs), ensuring strategic placement to minimize energy consumption and enhance operational efficiency. Constraints (15) to (16) ensure operational feasibility: Constraint (15) calculates travel time, Constraint (16) examines daily travel limits to prevent overuse, Constraint (17) defines binary variables, and Constraint (18) sets non-negative variable requirements. Constraints (19) and (20) address risk management and customer order conveyance, incorporating SORA approach to enhance safety. These constraints are critical for ensuring that UAV operations adhere to both regulatory standards and risk minimization goals, particularly in complex urban or sensitive airspace environments. Constraints (21) and (22) control the energy and capacity limits of UAVs, ensuring that energy consumption is optimized based on payload weight and route assignments. Constraints (23) and (24) further refine this optimization by accounting for UAV launch and recovery times, integrating these factors into effective travel duration calculations for trucks. For instance, the time required for UAV deployment and retrieval is factored into the truck's schedule, ensuring seamless coordination and minimizing energy wastage.

Constraint (25) ensures that if a UAV departs from node i, its arrival time at node j accounts for travel and recovery times, adhering to its flight endurance limits as detailed in Constraint (26). This coordination between UAV and truck operations enhances both energy efficiency and operational safety. Finally, Constraints (27) to (28) focus on total energy consumption, placing a cap on overall energy requirements to align with sustainability goals. Constraint (27) calculates the remaining battery energy after each leg, while Constraints (29) and (30) minimize total energy consumption based on cargo weight and routing assignments. These constraints not only improve system efficiency but also reduce the overall carbon footprint of the logistics network. By integrating these constraints, the model achieves a balance between operational efficiency, risk management, and environmental sustainability. This comprehensive approach confirms that the logistics system is both adaptable to diverse operational scenarios and aligned with broader sustainability and policy objectives, such as carbon-reduction targets and increased renewable energy adoption.

To ensure clarity and consistency throughout the mathematical formulation, Tables 3–5 summarize the key components of the proposed model. Table 3 introduces the notational sets, Table 4 describes model parameters including timing and cost variables, and Table 5 defines the binary and continuous decision variables.

3. Solution approach

This research addresses the NP-hard nature of the problem due to its scale and computational complexity by utilizing metaheuristic algorithms to optimize four key objectives, including environmental sustainability, within a reasonable timeframe. The NSGA-II algorithm was specifically chosen to solve the model, emphasizing the selection of the best solutions from each generation while maintaining a balance between operational efficiency and environmental objectives. A novel approach for generating the initial population was employed, based on the total number of demand points and UAVs, with detailed methodology outlined in subsequent sections. This approach ensures that initial solutions are not only diverse but also optimized for energy consumption and battery performance, contributing to the system's sustainability goals. NSGA-II offers significant advantages for this research, such as concurrent multi-objective optimization and fast convergence, making it ideal for large-scale, sustainability-focused searches. The algorithm efficiently handles non-penalty constraints, preserves solution diversity, and introduces elitism. These features are particularly beneficial for optimizing complex logistics systems, as they enable effective trade-offs between cost, time, risk, and energy consumption.

The algorithm optimizes the selection of UAV units, battery sizes, charging points, and distribution center assignments. Furthermore, it allocates UAVs to missions and tracks their whereabouts, guaranteeing that all decisions respect limitations such as the maximum battery power consumption per journey. The program directly lowers the logistics system's carbon footprint and complies with LCA guidelines by optimizing battery sizes and charging locations. A small-scale problem was initially resolved and evaluated in order to validate the model, demonstrating the algorithm's capacity to find environmentally friendly and energy-efficient solutions. The viability and sustainability optimization of UAV operations are guaranteed by NSGA-II's capacity to manage limits such as battery limitations and dynamic energy requirements. The NSGA-II algorithm was implemented in Python 3.11 and executed on a 64-bit Windows 11 system equipped with an Intel Core i7 processor (2.8 GHz) and 16 GB RAM. The algorithm was tested using a population size of 100 over 250 generations, which provided a good balance between convergence and diversity. The runtime for each scenario was roughly 9.2 min on average. The scalability and efficiency of the technique were demonstrated by the runtime's stability over several test cases. The NSGA-II procedure's flexibility allows for its useful use in actual urban logistics systems, providing insightful information for logistics planners and policymakers. By integrating advanced optimization techniques with real operational constraints, the model supports environmentally conscious and risk-informed delivery planning. Algorithm 1 provides the pseudocode for the algorithm, explaining its functionality, including inputs, outputs, and the step-by-step execution process.

Algorithm 1. Pseudocode of the NSGA II algorithms

Procedure NSGA-II with SORA Integration for Truck-Drone Delivery Model for Parameter s_{ij}^{k}
Inputs:
N: Population size
g: Number of generations
f: List of objective functions
Output:
The final population after g generations
Begin
1: Initialize Population P with size N
2: Infer $S_{ij}^{(k)}$ for the third objective function (e.g., delivery time, energy consumption, etc.) using SORA
3: Evaluate objectives for P using inferred $S_{ij}^{(k)}$
4: Sort P based on non-dominance into fronts, assign ranks
For $i = 1$ to g do
5: Generate Child Population Q from P
6: Apply genetic operators - Recombination and Mutation
7: Combine Parent and Child populations to form R
8: Infer $S_{ij}^{(k)}$ for R using SORA
9: Evaluate objectives for R, including the third objective using $S_{ij}^{(k)}$
10: Sort R based on non-dominance into fronts, assign ranks
11: Calculate the crowding distance for individuals in each front
12: Select the next generation population P from R based on rank and crowding distance until size N is filled
End For
End

To support the risk formulation logic, we adapt the Bayesian Belief Network (BBN)-based classification of RPAS risks introduced in Mahmoodi et al. (2025), as shown in Fig. 3. The diagram illustrates how various operational and technical risk sources are categorized under the SORA framework into Ground Risk Class (GRC) and Air Risk Class (ARC). These classifications feed into the model's computation of Specific Assurance and Integrity Levels (SAIL), which then define risk penalties and influence route constraints. While our model does not explicitly use BBN inference, the conceptual structure provides a transparent risk taxonomy for translating SORA elements into optimization components.

This risk classification framework directly informed the development of our third objective function, which minimizes the overall operational risk in the hybrid truck–UAV delivery model. Specifically, we quantified each UAV route's risk score by evaluating its exposure to the key factors outlined in the figure, such as proximity to urban areas, likelihood of

Table 3
Problem sets, variables, and parameters.

Sets	Description
D	A set of distributor candidate locations
N_0	A set of pickup nodes (Set of all possible departure nodes for a vehicle. F = {0, 1, …, n, $n+1$, …2n})
N	Set of nodes in the network (including depots). N = {0, 1, …, n, $n+1$, …2$n+1$}
N+	Set of all nodes a vehicle can visit. N+ = {1, 2, …, n, $n+1$, …2$n+1$}
F	Set of all pickup nodes. i ∈ F, F = {1, 2, …, n}
P	Set of all delivery nodes. j ∈ P, P = {$n+1$, $n+2$, …, 2n}
U	A set of UAVs
T	A set of Trucks

Table 4
Problem sets, variables, and parameters.

Parameters	Description
S_i^T	Time when truck t ∈ T to provide service to delivery nodes i
S_i^U	Time when UAV of truck t ∈ T reaches node i∈ $N_0 \cup N_+$ (minutes)
a_i^U	The earliest time UAV allowed to provide service to distributor in the hard time window
b_i^U	The latest time UAV allowed to provide service to distributor i in the hard time window
M	Optional large number
ES_i^U	The earliest time UAV allowed to provide service to distributor i in the soft time window
LS_i^U	The latest time UAV allowed for UAV to provide service to distributor i in the soft time window
a_i^T	The earliest time truck allowed to provide service to distributor i in the hard time window
b_i^T	The latest time truck allowed to provide service to distributor i in the hard time window
ES_i^T	The earliest time truck allowed to provide service to distributor i in the soft time window
LS_i^T	The latest time truck allowed to provide service to distributor i in the soft time window
α	Scaling factor for earliest start time deviation
β	Scaling factor for latest start time deviation
T_U	The time to end the route of UAV(U)
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
FC_U	Fixed cost of using UAV(U)
C	Cost of one charging unit
AT	Minimum amount of charging allowed inside the UAV (U)
DAY	The length of a working day
cp_{ji}	UAV battery consumption from node i to node j
d_{ij}	The distance between node i and node j
$full$	Battery charging capacity
V_U	The velocity of UAV (U)
S_{ij}^U	The risk of route deriving from node i to node j with UAV (U)
s_i	The time to start providing service to demand point i
E_i	The time deviation from the earliest time allowed to provide service to demand point i in the soft time window
L_i	The time deviation from the latest time allowed to provide service to demand point i in the soft time window
A_i	The amount of battery available on the UAV (U)
c_{ij}^U	Energy consumption for a UAV (U) to fly from location i to location j
C_U	Amortized cost of UAV (U)
C_{bat}^U	Amortized cost of the battery of UAV (U)
V_U	UAV speed
C_E	Cost of per unit of energy
n_U	Number of UAVs of type U a UAV operator can operate simultaneously
t_U^{bat}	Time required to replace the battery of UAV type U
l_i^U	The latest permissible time for a UAV to provide service at location i
l_j^U	The latest permissible time to provide service at delivery location j
l_i^T	The latest permissible time for a UAV to provide service at location i
l_j^T	The latest permissible time to provide service at delivery location j
t_{ij}	The travel time between locations i and j
e_i	Earliest possible pickup time
ch_U^o	Initial energy in the battery of UAV type U
ch_U^{min}	Minimum remaining energy required in the battery of UAV type U
ch_U^{max}	Maximum energy capacity of the battery for UAV type U
Δch_j	The additional charge gained at charging points
g_i	Remaining battery energy of a UAV after returning from delivery location i
g_i^t	Auxiliary variable storing the remaining battery energy after returning from delivery location i
f_i^U	Timing of when a UAV picks-up the package for delivery location i at depot
SL_U	Time needed to load UAV before launch (minutes)
SR_U	Time needed to recover UAV upon rendezvous (minutes)
V_T	Truck speed (miles per hour)
τ_{ij}	Time required by truck to move from node $i \in$ N0 to node $j \in$ N+ (minutes)
τ_{ij}^U	Analogous time for UAV (minutes)
C_{ij}^T	Cost for truck to travel from node $i \in$ N0 to $j \in$ N+ ($)
C_{ij}^U	Cost to operate UAV between nodes $i \in N_0$, $j \in C'$ and $B \in N^+$ ($)
D^T	Truck service duration at node $i \in$ N (minutes)
D^U	UAV service duration at node

Table 5
Problem sets, variables, and parameters.

Decision Variables	Description
x_{ij}^T	1 if truck t ∈ R moves between nodes $i \in N_0$ and $j \in N^+$ where $i \neq j$, 0 otherwise.
y_{ij}^{TU}	1 if UAV of truck T ∈ R departs from node $i \in N_0$, flies to $j \in$ C and returns to the end depot or truck at node $B \in N^+$, 0 otherwise.
z_{ij}	1 if delivery location i is served immediately before j by a UAV, 0 otherwise
y_i	1 if UAV battery is replaced after returning from delivery location i, 0 otherwise
x_{ki}	1 if UAV type U is assigned to deliver a package to location i, 0 otherwise
Y_{ij}	Binary variable indicating whether a UAV travels from point i to a point j

system failures, and environmental hazards. Each element from the SORA-based taxonomy was mapped to numerical indices within the model: ARC affected airspace constraint severity, GRC were linked to population density zones, and SAIL levels determined the required mitigation measures. These were incorporated as weighted penalty terms in the risk objective function, allowing the model to evaluate trade-offs between energy, time, and risk. This approach provides a systematic and operational translation of SORA steps into mathematical constraints and optimization logic, fulfilling safety assurance requirements in complex logistics scenarios.

4. Results and discussions

4.1. Results of the multi-objective evolutionary algorithm (MOEA)

Table 5 outlines the performance metrics across 250 generations. As the generations progress, several key indicators in the table demonstrate a general trend towards improvement. Initially, the average objective value starts at 531,442.5 and steadily decreases, reflecting enhanced solutions, and ultimately stabilizes around 511810.5 in generation 250. This reduction in the average value signifies the algorithm's success in refining the solutions to optimize the objective function. Similarly, the standard deviation (Std) decreases significantly from 5941.4 to 386.2, indicating that the solutions are becoming more consistent and less dispersed over the generations.

Moreover, in generation 0, 50 evaluations were conducted with an average objective value of 531,442 and a standard deviation of 5941.44. The objective values ranged from 517,073 to 543,248. The average operational cost was 531,944, service time was 531,252, risk index was 530,787, and overall Battery usage was 531,787. This information demonstrates how the algorithm progresses and moves towards optimizing the objective function in each generation. Over time, the average and minimum objective values decrease, indicating improved algorithm performance. Further, the average operational cost and service time both show a consistent downward trend, suggesting improvements in efficiency and performance. The risk index also follows a similar declining pattern, signifying that the algorithm effectively reduces the risk associated with the solutions as the generations advance. The minimum objective value and maximum objective value also reduce from their initial values, showing that not only are the average solutions improving, but the best solutions within each generation are getting closer to the optimal. Overall, the genetic algorithm demonstrates its capability to evolve the population towards more optimal solutions

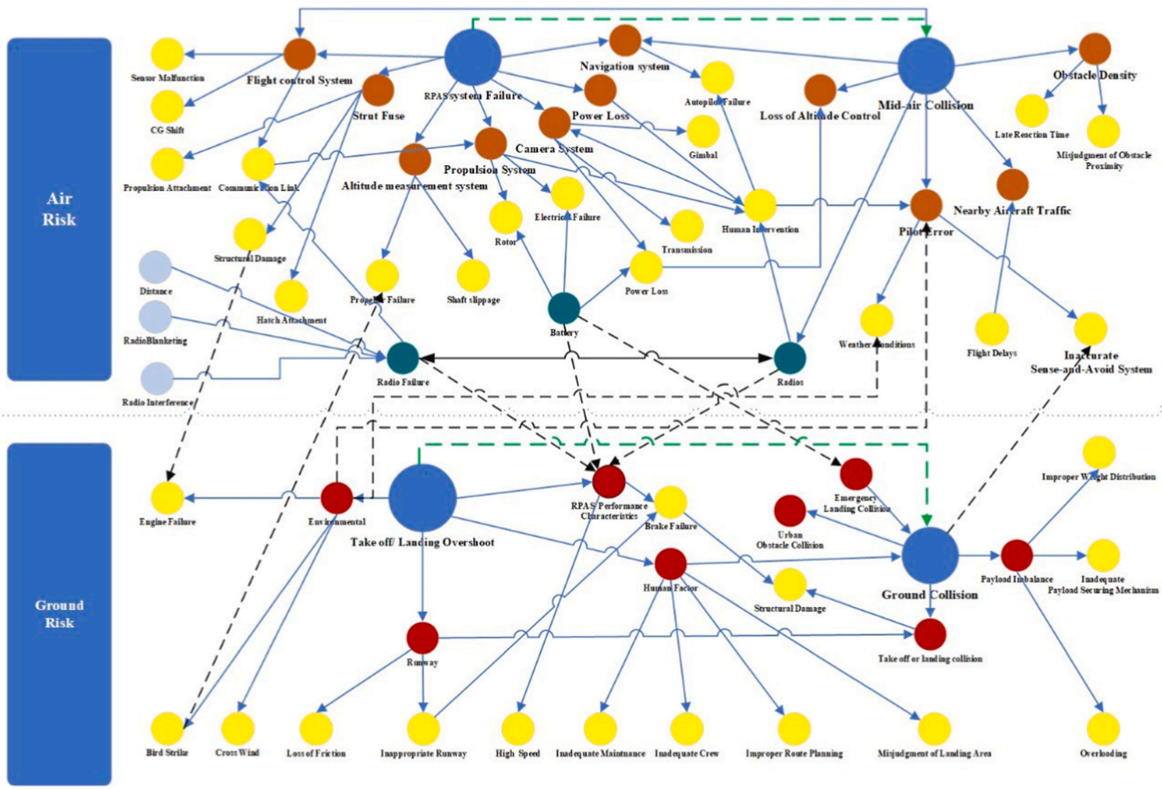


Fig. 3. Bayesian-based mapping of UAV system risks under the SORA framework, adapted from Mahmoodi et al. (2025).

through successive generations, reducing both costs and risks while enhancing operational performance.

4.2. Analysis of convergence behavior of objective functions

This section focuses on the analysis of the convergence behavior of the objective functions over multiple generations during the optimization process.

Table 6 presents multi-objective optimization data over several generations, showing key metrics such as operational cost (OC), service time (ST), risk index (RI), and battery usage (BU) at different generation intervals (0, 50, 100, 150, 200). The table includes additional statistical information like the average, standard deviation (Std), minimum (Min), and maximum (Max) values for each generation. The number of evaluations (Nevals) indicates the number of solutions evaluated per generation. As seen in the data, values tend to stabilize after a few generations, indicating convergence towards optimal solutions across the objectives. As seen in the graphs, each of the objective functions cost, time, risk, and battery usage undergoes a period of fluctuations before stabilizing. For instance, the cost fluctuates between 7.5 and 8 million during the initial generations, indicating variability in the optimization process. After generation 57, the system achieves stability, with the cost settling at around 4.5 million. Similarly, time, risk, and battery usage also experience initial variability before reaching convergence, suggesting the effectiveness of the optimization algorithm in balancing the trade-offs among these objectives.

Fig. 4 illustrates the convergence trends of four objective functions: cost, time, risk, and battery usage, over generations. Initially, significant fluctuations are observed in all metrics, reflecting instability in the early stages of optimization. Cost fluctuates between 7.5 and 8 million before fixing at 4.5 million after generation 57. Time reduces from a range of 101,000–105,000 to 95,000 by generation 30, while risk decreases from 800,000 to 900,000 to 700,000 after generation 45. Likely, battery usage fluctuates between 5000 and 7000 units before stabilizing at 4500 units after generation 68. These patterns indicate that the optimization algorithm effectively reduces variability and improves performance across all objectives, reaching stable, optimal solutions for cost, time, risk, and energy consumption after specific iterations.

Fig. 5 illustrates a heatmap reflecting the correlation between four objective functions, using a color scheme based on the Viridis palette. The color gradient moves from deep purple (indicating negative correlations close to −1) to bright yellow (indicating strong positive correlations close to 1). Notably, there is a strong positive correlation of 0.7 between operational cost and service time, suggesting that as service time increases, operational costs also tend to rise. This relationship highlights the trade-off between efficiency and cost, underscoring the importance of leveling these objectives in logistics planning. The correlation between risk index and battery usage (0.46) indicates that higher battery usage may introduce moderate risks, likely due to operational constraints or increased energy demands. Conversely, negative correlations are observed between battery usage and both operational cost (−0.56) and service time (−0.74), demonstrating that efficient battery management can significantly reduce costs and improve service times. Similarly, the risk index's negative correlation with operational cost (−0.37) and service time (−0.45) implies that risk tends to decrease when costs and service times are minimized. These insights are critical for integrating sustainability into logistics systems, as they reveal how optimizing battery usage can simultaneously address cost and efficiency objectives.

For further analysis, Fig. 6 presents a 3D trade-off plot representing the relationships between four key objectives: Cost, Time, Risk, and Battery Consumption. Each point on the plot corresponds to a solution, with its position determined by cost, time, and risk values, while the color gradient indicates battery consumption levels. The plot reveals a clustering of blue points (indicating low cost and time) near the bottom-left corner, where battery consumption is higher. This suggests that higher battery usage often correlates with reduced operational costs and shorter service times, emphasizing the environmental and operational

Table 6
The output performance of the proposed NSGA-II algorithm.

Gen	Nevals	Avg	Std	Min	Max	OC	ST	RI	BU
0	50	531142.5	5941.443	517073.2	543247.8	531944.1	531251.8	530787.3	531786.7
50	91	525440.2	3140.813	523905.2	525941.2	531251.8	525250.7	524781.3	525786.7
100	90	521476.4	2137.936	517072.2	524912.2	521642	521642.4	520794.2	521836.7
150	89	518451.2	1969.965	509992.2	520495.2	518997.9	518297.6	517764.6	518812.5
200	90	516083.1	2585.133	508304.2	518391.2	516627.7	515882.8	515824.7	516400.6
250	91	511810.5	2444.836	506050.2	516638.2	511599.7	511599.7	511150.9	512144.1

benefits of energy-efficient strategies. Conversely, solutions with higher costs and time appear to have lower battery consumption, as indicated by red points scattered further from the origin. This inverse relationship highlights the need for careful planning to balance energy usage with cost and time objectives. Interestingly, the risk index shows variability across solutions without a clear correlation with battery consumption, suggesting that optimizing battery-related objectives may not directly address risk. This finding underscores the complexity of achieving a holistic optimization that balances all objectives.

By combining insights from Figs. 5 and 6, decision-makers can prioritize objectives based on specific constraints or project goals. For instance, scenarios emphasizing cost and time reductions may focus on increasing battery efficiency, while those prioritizing risk management may require additional strategies beyond battery optimization. These analyses not only provide actionable frameworks for optimizing logistics operations but also contribute to broader sustainability goals by highlighting the potential of reducing carbon footprints through efficient energy management and multi-objective optimization. Furthermore, aligning these results with LCA principles ensures that the environmental benefits extend beyond immediate operational gains, supporting long-term sustainability in logistics systems. The following visualizations (Figs. 6–8) are based on absolute performance values and aim to illustrate the trade-offs between the four objectives. Units are explicitly included to improve interpretability.

Fig. 7 represents multi-objective optimization results, comparing various objectives such as operational cost, service time, risk index, and battery usage. These six 2D trade-off plots provide a detailed visual comparison of different pairs of objectives derived from the 3D trade-off model. Each plot displays data points representing solutions, with colors indicating battery consumption. This visualization enables decision-makers to explore how objectives interact and identify balanced solutions based on specific priorities. The first plot shows the relationship between Risk Index and Battery Consumption, revealing a relatively

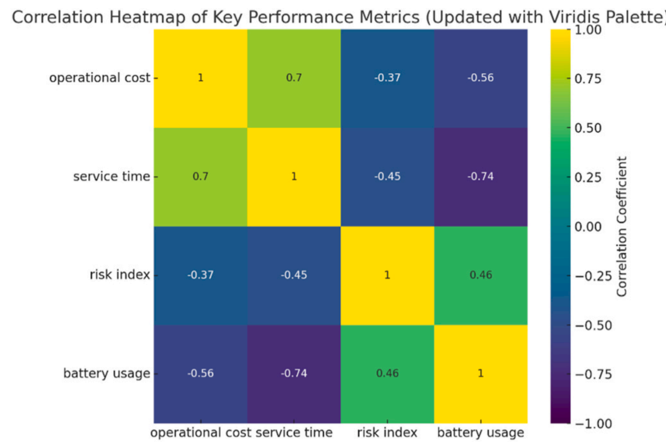


Fig. 5. Correlation of key performance metrics.

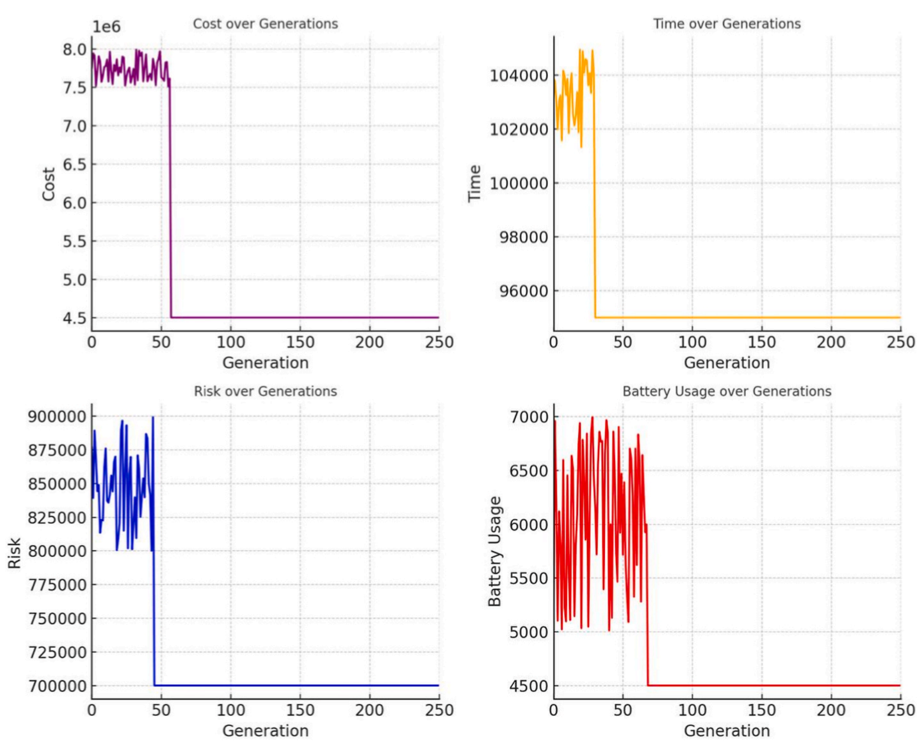


Fig. 4. Fitness across different generations.

even spread of battery consumption values across different risk levels. This indicates that risk does not have a strong direct correlation with battery usage. Solutions with both high and low battery consumption are observed across various risk levels, suggesting that battery optimization may not directly influence risk minimization. This finding highlights the importance of employing separate strategies to address energy efficiency and risk management. The second row of plots examines the relationships between Cost and both Risk and Time. The Cost vs Time plot exhibits a scattered relationship, where no clear trend emerges between these two objectives. Both low-cost and high-cost solutions display varying time requirements, suggesting that optimizing cost does not necessarily result in better time efficiency and vice versa. In contrast, the Risk vs Cost plot shows a slightly noticeable trend where higher costs are associated with a lower risk index, although this relationship is not strong. This underscores the potential trade-offs between safety and financial efficiency.

Clear trade-offs between the goals were identified by the Pareto analysis: reducing delivery time frequently results in higher energy consumption, but reducing operating costs may raise risk by choosing more convoluted or insecure routes. For instance, a quick delivery route that uses UAVs to avoid traffic jams would use more batteries and necessitate riskier airways. The necessity to rank goals according to certain operational settings is highlighted by these trade-offs. Energy optimization methods like battery allocation should be separated from risk management measures like SORA-informed path planning to preserve efficiency without sacrificing safety. It is crucial to remember that risk management and energy consumption provide two essentially different problems in UAV-based logistics. Strategies like adaptive charging scheduling, effective battery allocation, and route simplification to reduce power consumption are commonly used to optimize energy utilization. On the other hand, risk management emphasizes avoiding dangerous areas, adhering to airspace rules, and making SORA-informed route choices in order to guarantee operational safety. Therefore, these goals necessitate distinct but coordinated strategies. Future advancements could improve total system resilience without sacrificing energy efficiency by integrating dynamic battery management systems with real-time risk mapping.

The remaining comparisons, including Battery Consumption vs Time and Cost vs Battery Consumption, provide further insights into the system's energy dynamics. The Battery Consumption vs Time plot reveals that solutions with lower battery consumption also tend to have

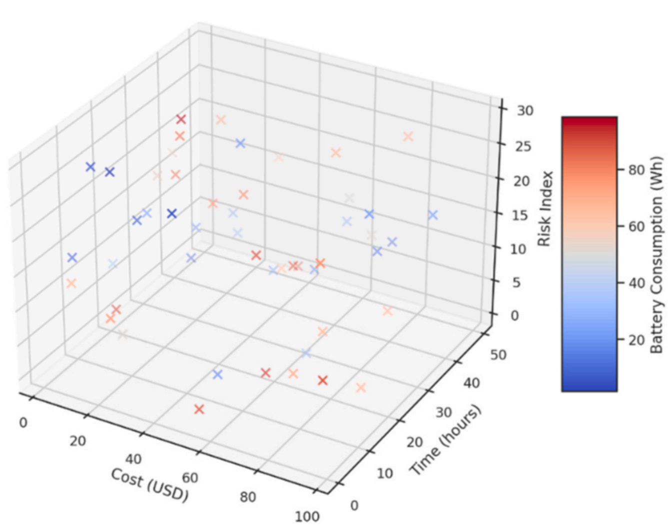


Fig. 6. 3D Visualization of Objective Trade-offs: Service Time (hours), Operational Cost (USD), and Risk Index, with Battery Consumption (Wh) represented through color gradient. All values are in absolute terms. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

shorter time requirements. Conversely, longer time durations are associated with higher battery usage, indicating a trade-off between energy consumption and delivery time. This finding emphasizes the need to balance operational efficiency with energy sustainability, particularly in scenarios where energy resources are constrained. The Cost vs Battery Consumption plot indicates that higher costs generally correlate with higher battery consumption. This suggests that costlier solutions often involve more resource-intensive options, potentially leading to higher environmental impacts. By integrating this insight into decision-making, strategies can be devised to minimize costs while reducing energy consumption, thus contributing to broader sustainability goals. To sum up, these trade-offs provide actionable insights for decision-makers aiming to balance multiple objectives. For instance, projects prioritizing time efficiency may focus on minimizing battery consumption, while those emphasizing cost reductions might explore solutions with moderate energy usage. Furthermore, aligning these results with LCA principles ensures that the environmental benefits of optimized solutions extend across the system's entire lifecycle, from deployment to disposal. This approach not only supports immediate operational goals but also fosters long-term sustainability in logistics systems.

Fig. 8 presents the distribution of fitness values for four different objective functions: operational cost, service time, risk index, and battery usage. Each objective shows a distinct range of fitness values, highlighting variability in performance. Notably, the fitness values for operational cost and battery usage are relatively higher compared to service time and risk index, suggesting that these objectives might be optimized differently or have a higher baseline value. This observation emphasizes the importance of aligning cost and battery optimization with sustainability goals, as these metrics directly influence the system's environmental impact. The distributions for operational cost and battery usage exhibit a tight interquartile range with minimal outliers, indicating consistent performance across samples. This stability reflects the effectiveness of the optimization process in minimizing energy consumption and costs, contributing to a reduced carbon footprint. On the other hand, service time and risk index demonstrate a lower range of fitness values with a more compact distribution, signifying that these objectives result in less variance and possibly better consistency in optimization outcomes. Such consistency is particularly valuable for ensuring reliable operations in logistics systems while adhering to risk management standards like SORA.

This analysis provides valuable insights into the trade-offs and optimization stability across different objectives. For instance, the tight distribution of battery usage suggests that the optimization process successfully balances energy efficiency with operational constraints, aligning with LCA principles. Meanwhile, the compact distribution of risk index highlights the model's robustness in managing safety concerns across diverse scenarios. From a practical perspective, decision-makers can leverage these insights to prioritize objectives based on project-specific goals. For example, scenarios emphasizing sustainability may focus on optimizing battery usage and operational cost, while those requiring high reliability might prioritize risk and service time. Furthermore, the stability of fitness values for key objectives underscores the model's applicability to real-world logistics operations, offering a framework for designing energy-efficient and environmentally sustainable delivery systems. By integrating this analysis into broader optimization strategies, businesses and policymakers can develop logistics systems that not only meet operational demands but also support long-term sustainability objectives. This approach ensures that environmental benefits are realized throughout the system's lifecycle, from implementation to decommissioning, reinforcing the importance of energy-efficient optimization in achieving a sustainable logistics future. The optimization of the risk objective reveals clear quantitative trade-offs between safe airspace routing and operational performance (cost and time), a relationship largely unexplored in previous truck–drone models and rarely captured in existing UAV optimization literature.

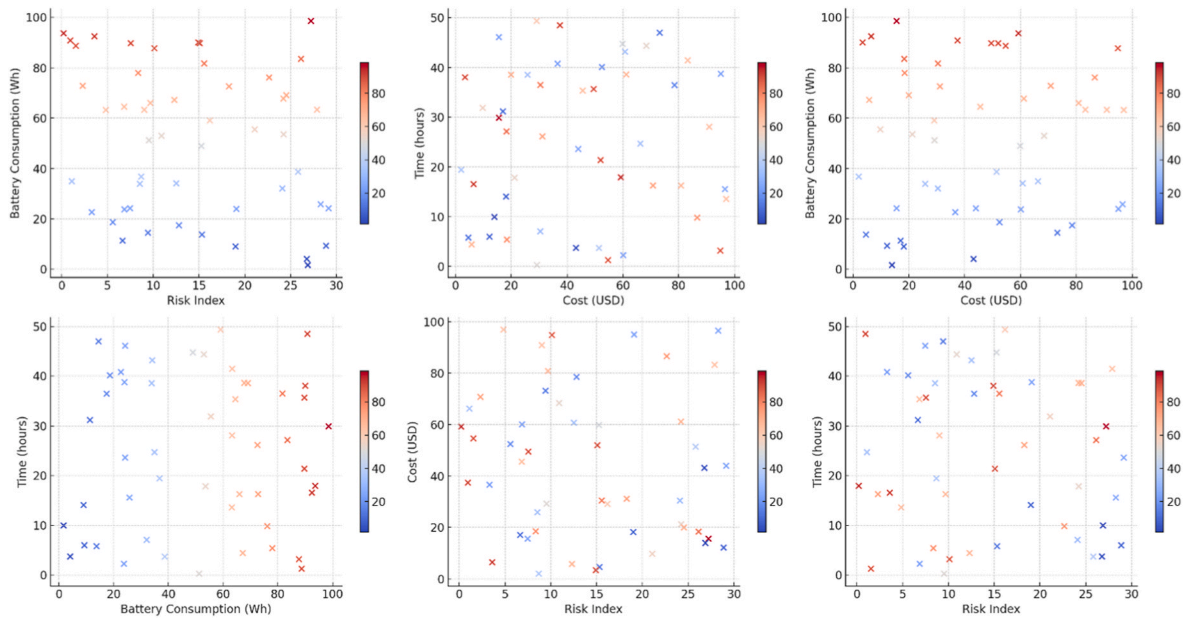


Fig. 7. 2D Scatter Plots Showing Pairwise Trade-offs Among Service Time (hours), Operational Cost (USD), Risk Index, and Battery Consumption (Wh). All values are absolute.

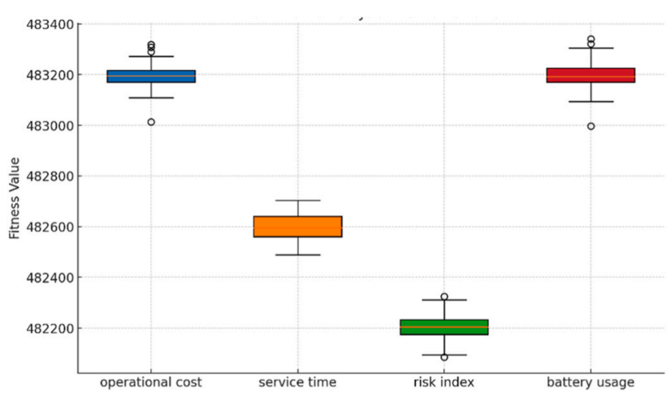


Fig. 8. Boxplot comparison of objective function distributions: Operational cost (USD), service time (hours), risk index, and battery usage (Wh).

Fig. 9 illustrates the optimal delivery routes for a logistics system involving both trucks and UAVs. The depot serves as the central hub, marked in blue, with multiple distributors and facilities highlighted in red and green, respectively. The UAVs operate between the depot, distributors, and charging points, shown in purple, while the trucks follow distinct paths to ensure optimal coverage of the delivery network. This multi-vehicle approach not only enhances operational efficiency but also aligns with sustainability goals by reducing energy consumption and carbon emissions. The inclusion of two trucks and two UAVs creates a dynamic and adaptive delivery system where tasks are shared to minimize delivery times and energy usage. The two truck routes, displayed in red and cyan, indicate unique paths across the logistics network. Truck Route 1 covers a path from the depot to several distributors and facilities, while Truck Route 2 follows a different trajectory to maintain coverage in other areas. This strategic separation of routes avoids redundant paths, optimizes fuel use, and ensures efficient delivery operations. Additionally, truck routes incorporate key charging points, enabling sustained operations over long distances and supporting the integration of renewable energy sources for charging.

UAV routes, represented by dashed blue and green lines, provide faster deliveries between demand points that are farther from the depot. These UAVs utilize strategically placed charging stations to recharge their batteries, allowing them to operate efficiently over extended distances without frequent returns to the depot. By covering areas that would be less efficient for ground-based vehicles, UAVs complement the trucks and enhance overall network performance. This system design achieves a balance between operational efficiency and environmental sustainability. By leveraging UAVs for shorter, more direct deliveries and trucks for broader coverage, the system reduces total delivery time and minimizes fuel consumption. Together, these multi-vehicle routes form an efficient logistics framework that not only improves delivery performance but also significantly lowers carbon emissions. From a life-cycle perspective, the optimized delivery routes contribute to reducing the environmental impact of the logistics system by ensuring energy-efficient operations throughout the supply chain. This alignment with LCA principles underscores the potential for sustainable logistics solutions that integrate advanced vehicle routing strategies. In practical terms, decision-makers can use this system design to develop sustainable logistics strategies tailored to specific operational contexts. For example, integrating renewable energy sources at charging points or scaling the system for larger networks could further enhance sustainability. This approach provides a robust framework for policymakers and businesses aiming to meet carbon reduction targets while maintaining high levels of service efficiency.

In our NSGA-II implementation, all four objectives operational cost, service time, risk index, and energy consumption were treated with equal weight, reflecting a balanced approach to performance, safety, and environmental sustainability. No domain-specific prioritization was imposed to avoid biasing the Pareto search space. As illustrated in Figs. 6 and 7, trade-off patterns clearly emerge; for example, minimizing service time may lead to increased risk levels, while reducing cost could elevate energy consumption. The 3D and 2D visualizations highlight the inherent conflicts among objectives, enabling stakeholders to select solutions that best suit their operational preferences. These visual trade-off analyses, together with convergence behavior in Fig. 4 and data in Table 5, demonstrate the algorithm's effectiveness in navigating multi-criteria conflicts without requiring pre-defined weights.

5. Sensitivity analysis

In this section, a comprehensive sensitivity analysis is performed to evaluate the impact of various factors Drone Efficiency, Number of

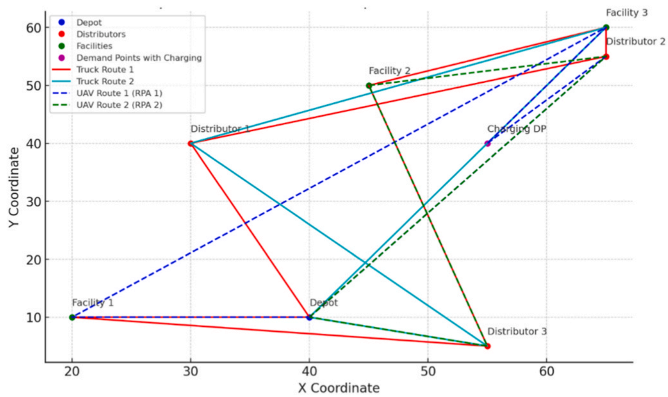


Fig. 9. Optimal route Configuration between facility locations, distributors, and demand points in UAV and truck logistics network.

Vehicles, Energy Consumption, and Confidence Levels on the four main objectives of the logistics system: Operational Cost, Delivery Time, Risk Index, and Energy Consumption. Each factor's influence is analyzed individually and in pairwise comparisons, providing valuable insights into the system's performance under diverse conditions. The findings are accompanied by relevant figures for clarity and better understanding.

5.1. Impact of Drone Efficiency on Objectives

Drone efficiency is a critical determinant of the operational effectiveness and environmental sustainability of drone-based delivery systems. As drone efficiency improves, all four objectives undergo massive changes, particularly in energy consumption and operational costs. Fig. 9 shows the impact of diversity drone efficiency (60 %, 70 %, 80 %, 90 %, and 100 %) on Operational Cost, Delivery Time, Risk Index, and Energy Consumption.

Operational Cost: Increased drone efficiency reduces operational costs by minimizing energy requirements and optimizing route planning. This directly aligns with sustainability objectives by lowering the system's overall energy demand and associated carbon footprint.

Delivery Time: As drone efficiency improves, delivery times decrease due to faster travel and reduced need for frequent charging. This highlights the potential of efficient drones to enhance service reliability while supporting energy conservation.

Risk Index: Higher efficiency levels reduce the Risk Index by improving operational predictability and lowering the likelihood of system failures. This demonstrates the importance of incorporating robust drones in high-risk scenarios, especially in urban or regulated airspaces.

Energy Consumption: Enhanced efficiency directly correlates with lower energy consumption, emphasizing the role of energy-efficient technologies in achieving sustainability goals. This improvement supports LCA principles by reducing the environmental impact of the system throughout its operational lifespan. These findings underscore the significance of investing in advanced drone technologies to optimize system performance across multiple objectives while reducing environmental impacts.

Table 7 outlines the quantitative effects of increasing drone efficiency on four primary objectives: Operational Cost, Delivery Time, Risk Index, and Energy Consumption. The results highlight a clear trend: as drone efficiency improves, all performance metrics experience significant gains, emphasizing the value of energy-efficient technologies in logistics systems. At 60 % drone efficiency, the system exhibits suboptimal performance, with operational costs at 15,400, a delivery time of 0.022, a Risk Index of 54.12, and energy consumption of 110.5 kWh. These values reflect higher energy demands and operational inefficiencies, which directly translate to increased carbon emissions and resource usage. As drone efficiency increases to 70 %, notable improvements are observed. Operational costs decrease to 13,300, delivery time improves to 0.019, the Risk Index reduces to 48.30, and energy consumption drops to 98.7 kWh. These changes demonstrate the potential for immediate energy savings and cost reductions through moderate efficiency enhancements.

At 80 % efficiency, the system achieves further improvements, with operational costs dropping to 11,700, delivery time shortening to 0.017, the Risk Index reducing to 43.56, and energy consumption decreasing to 88.9 kWh. These values highlight the compounding benefits of enhanced efficiency, particularly in terms of energy savings, which contribute to reduced carbon footprints. At 90 % efficiency, the metrics improve significantly: operational costs drop to 10,100, delivery time reduces to 0.014, the Risk Index lowers to 38.12, and energy consumption decreases to 77.4 kWh. Finally, at 100 % efficiency, the system achieves optimal performance, with the lowest operational costs of 8,900, the shortest delivery time at 0.012, the lowest Risk Index at 34.25, and minimal energy consumption at 68.5 kWh. These results underscore the strong relationship between drone efficiency and overall system sustainability. By reducing energy consumption, the system not only achieves cost-efficiency and speed but also minimizes its environmental impact. From a LCA, these achievements grant to long-term sustainability by decreasing the energy demands and emissions associated with logistics operations.

This analysis provides actionable insights for decision-makers aiming to optimize logistics systems while meeting sustainability goals:

1. Upgrading Drone Technologies: backing in high-efficiency drones can yield significant cost and energy savings, reducing the system's environmental footprint.
2. Incentivizing Energy Efficiency: Policymakers can use these results to design incentives or subsidies for adopting energy-efficient logistics technologies.
3. Strategic Fleet Management: Businesses can leverage these findings to balance fleet size and efficiency, ensuring both operational and environmental objectives are met.

By integrating these insights into decision-making, logistics systems can transition towards more sustainable and energy-efficient operations, supporting broader carbon reduction and resource conservation efforts.

Figs. 10 and 11 highlight the significant improvements achieved by increasing drone efficiency from 60 % to 100 %, demonstrating consistent reductions in operational cost, delivery time, risk index, and energy consumption. As efficiency improves, operational costs steadily decline due to optimized resource usage, while delivery times shorten as faster drones enhance service reliability. The risk index decreases with improved efficiency, reflecting safer operations and better compliance with methodology like SORA. Notably, energy consumption shows the most significant reduction, underscoring the environmental benefits of high-efficiency drones in minimizing carbon footprints and supporting LCA principles. These findings emphasize the dual benefits of operational efficiency and sustainability, offering actionable insights for decision-makers to invest in energy-efficient drones, design policies promoting sustainable logistics, and strategically optimize delivery systems for both cost-effectiveness and environmental impact reduction.

In Fig. 11, the sensitivity analysis reveals significant benefits of

Table 7
Impact of drone efficiency on operational cost, delivery time, risk index, and energy consumption.

Drone Efficiency (%)	Operational Cost	Delivery Time	Risk Index	Energy Consumption
60	15400	0.022	54.12	110.5
70	13300	0.019	48.3	98.7
80	11700	0.017	43.56	88.9
90	10100	0.014	38.12	77.4
100	8900	0.012	34.25	68.5

increasing drone efficiency across various objectives in the logistics system. The comparison between Operational Cost and Risk Index shows a clear downward trend for both metrics as drone efficiency rises. This indicates that improving drone efficiency aligns cost savings with enhanced safety, offering a dual advantage of economic benefits and operational reliability. Similarly, the comparison between Operational Cost and Delivery Time demonstrates that more efficient drones lead to quicker deliveries at reduced costs. This relationship underscores the potential for achieving high levels of operational performance while minimizing energy use, which directly contributes to sustainability goals. The analysis also highlights the interaction between Delivery Time and Energy Consumption, where higher drone efficiency significantly reduces both metrics. Faster delivery times achieved with efficient drones result in lower idle energy usage, supporting both economic and environmental objectives. Additionally, the relationship between Risk Index and Energy Consumption shows that as drones become more efficient, safety improves, and energy usage declines. This finding emphasizes the ability to simultaneously enhance safety and energy efficiency, merging operational and environmental priorities seamlessly.

These trends provide valuable insights for decision-making in logistics systems. By adopting high-efficiency drones, businesses can reduce costs, delivery times, and risks while promoting energy efficiency, thereby aligning with broader carbon reduction and sustainability initiatives. Policymakers can leverage these findings to create incentives for energy-efficient technologies and renewable energy integration in logistics systems. Moreover, by aligning these optimizations with LCA principles, organizations can ensure that operational improvements translate into long-term environmental benefits, fostering a more sustainable logistics future.

5.2. Impact of Number of Vehicles on Objectives

The availability of vehicles, including drones and trucks, significantly impacts the overall efficiency and performance of logistics operations. Table 8 illustrates how varying the number of available vehicles, ranging from 10 to 50 drones, affects four primary objectives: Operational Cost, Delivery Time, Risk Index, and Energy Consumption. As fleet size increases, operational costs and delivery times decrease due to better task distribution and optimized resource utilization. Larger fleets reduce redundancies in delivery routes, improving cost efficiency while shortening delivery times. Additionally, the Risk Index declines with more vehicles, reflecting enhanced operational reliability and reduced likelihood of delays or failures. These improvements are particularly beneficial in high-risk or regulated environments where safety and consistency are crucial. From a sustainability perspective, increasing fleet size promotes energy efficiency by distributing energy-intensive tasks across multiple drones, reducing strain on individual vehicles. This trend contributes to lower overall energy consumption, aligning with LCA principles by minimizing carbon emissions and

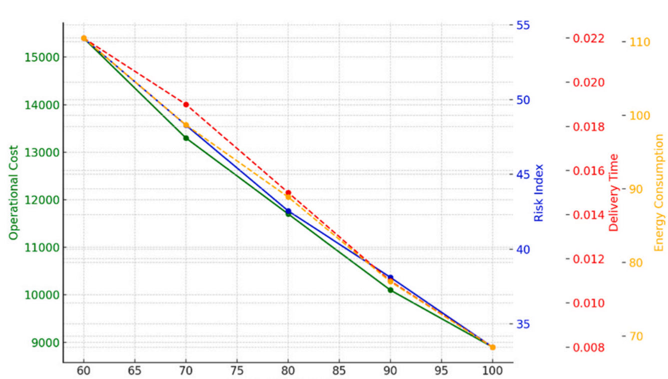


Fig. 10. Impact of drone efficiency on objectives.

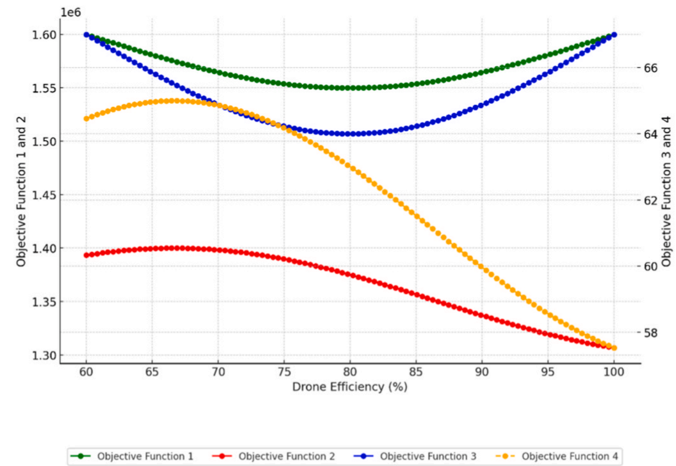


Fig. 11. Pairwise comparisons of objectives.

resource depletion over the system's lifespan. Businesses can use these findings to optimize their fleets for operational and environmental performance, while policymakers can incentivize the adoption of larger, energy-efficient fleets through subsidies or tax benefits. By integrating renewable energy sources into charging infrastructure, the scalability of such systems can further enhance their environmental benefits, ensuring long-term sustainability in logistics networks.

Table 8 highlights the impact of fleet size on key objectives: Operational Cost, Delivery Time, Risk Index, and Energy Consumption. The data shows that increasing the number of vehicles leads to significant improvements across all objectives. With 10 vehicles, operational costs are at their highest (17,000), delivery time is slowest (0.025), the Risk Index is elevated (60.23), and energy consumption peaks at 115.6 kWh. As fleet size expands to 20, 30, 40, and 50 vehicles, these metrics improve progressively, with operational costs dropping to 8,200, delivery time shortening to 0.010, the Risk Index reducing to 33.21, and energy consumption declining to 67.3 kWh. These trends reflect the enhanced efficiency of larger fleets, where tasks are distributed more evenly, reducing redundancy and optimizing resource usage. The consistent reduction in energy consumption and delivery times highlights the scalability of the system and its capacity to meet demand more sustainably.

From an environmental perspective, the results underscore the significant benefits of fleet expansion in reducing carbon emissions and energy consumption. Lower energy usage per vehicle, achieved through effective task distribution, aligns with sustainability goals and supports LCA principles by minimizing the system's environmental footprint. These findings provide actionable insights for businesses and policymakers: companies can strategically expand their fleets to balance cost, efficiency, and sustainability, while governments can design incentives to promote the adoption of energy-efficient fleets, such as subsidies for integrating renewable energy solutions. By adopting these strategies, logistics systems can achieve both operational excellence and long-term environmental benefits, making them more resilient and sustainable in the face of growing global demand.

Fig. 12 illustrates the impact of increasing the fleet size on four key objectives: Operational Cost, Risk Index, Delivery Time, and Energy Consumption. As the number of vehicles grows from 10 to 50, operational costs and energy consumption decline significantly due to optimized route allocation and efficient distribution of tasks across the fleet, directly contributing to reduced carbon emissions. Delivery times improve as additional vehicles enable faster, parallel deliveries, enhancing system efficiency and customer satisfaction. The Risk Index also decreases, reflecting improved safety through balanced workloads and minimized system failures. These trends emphasize the environmental and operational benefits of fleet expansion, aligning with LCA

Table 8
Impact of fleet size on operational cost, delivery time, risk index, and energy consumption.

Number of Vehicles	Operational Cost	Delivery Time	Risk Index	Energy Consumption
10	17000	0.025	60.23	115.6
20	14300	0.02	53.14	100.5
30	11800	0.015	45.34	89.2
40	9600	0.012	38.75	75.9
50	8200	0.01	33.21	67.3

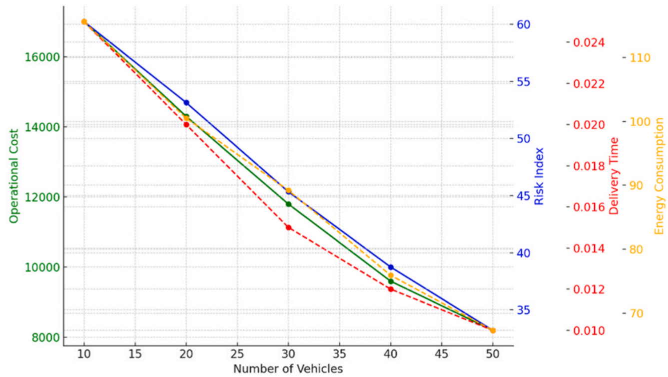


Fig. 12. Impact of number of vehicles on objectives.

principles by reducing energy demands and promoting long-term sustainability. This analysis underscores the critical role of strategic fleet scaling in achieving both economic efficiency and environmental responsibility.

Fig. 13 illustrates the impact of increasing the number of vehicles on four objective functions, highlighting trade-offs between operational efficiency and environmental or risk-related factors. Objective Function 1 (green line), representing cost or time, decreases steadily with fleet expansion, reflecting improved resource allocation and reduced inefficiencies. Objective Function 3 (blue line), linked to energy consumption, also declines, emphasizing enhanced energy efficiency and reduced carbon emissions. In contrast, Objective Function 4 (orange line), potentially representing environmental cost or risk, increases, suggesting challenges such as higher emissions or operational complexity with larger fleets. Objective Function 2 (red line) remains stable, indicating minimal sensitivity to fleet size. These patterns underscore the importance of balancing objectives to optimize logistics systems, where increased fleet size can improve cost and energy

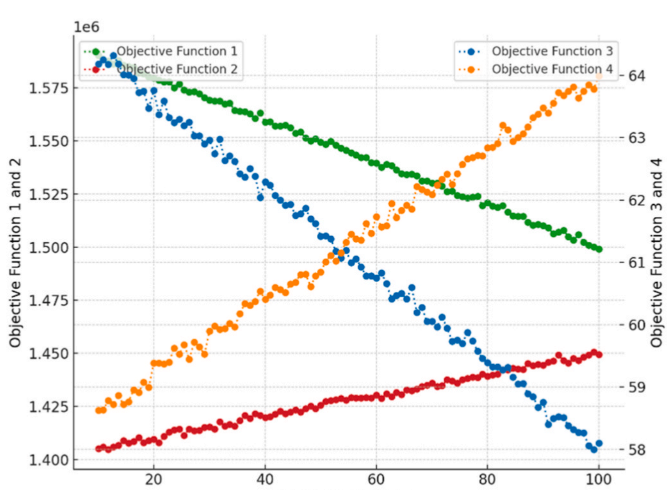


Fig. 13. Pairwise comparisons of objectives.

efficiency but may require strategies to mitigate associated risks or environmental impacts. Integrating renewable energy sources and adopting energy-efficient vehicles can help align operational and sustainability goals, ensuring long-term benefits.

5.3. Limitations

While the proposed framework effectively integrates cost, time, risk, and energy consumption objectives within a hybrid truck–drone logistics model, it is important to acknowledge limitations related to real-world operational complexities. With predetermined infrastructure availability and specified UAV energy characteristics, the model functions under idealized assumptions. Not all factors are taken into account, including topographical restrictions, dynamic urban traffic, weather variations, and legislative restrictions, particularly with regard to beyond visual line-of-sight (BVLOS) activities. In real-world situations, these variables can have a big impact on UAV route dependability, battery drain rates, and overall service viability. Moreover, the current paradigm does not take emergency rerouting or unpredictable journey durations brought on by air traffic conditions into consideration.

Additionally, the integration of SORA-based risk considerations, while operationally meaningful, does not yet capture all real-time safety challenges such as transient population movements, unexpected ground risk fluctuations, or dynamic no-fly zones. Embedding these stochastic safety dynamics into the optimization process represents an important future direction for enhancing the practical robustness of hybrid delivery systems. The model assumes fixed-grid charging and overlooks renewable energy options, though solar- or hybrid-powered droneports could enhance sustainability, especially in off-grid areas. Future work should explore adaptive energy solutions like battery swapping and solar-based scheduling. These improvements would enhance the model's feasibility and bring it closer to long-term decarbonization objectives and LCA concepts.

6. Conclusions

This study presents a multi-objective optimization framework for hybrid truck-drone delivery systems, addressing operational inefficiencies, environmental sustainability, and risk management challenges. By extending the VRPPD and the FSTSP, the model integrates advanced features such as battery consumption optimization, CO2 emissions reduction, and comprehensive sustainability evaluation. Using a MILP approach combined with the NSGA-II, the framework optimizes key objectives, including operational costs, delivery times, energy consumption, risk, and battery performance. Numerical results demonstrate significant improvements as drone efficiency and fleet size increases. For instance, when drone efficiency increases from 60 % to 100 %, operational costs decline from 15,400 to 8,900, delivery times reduce from 0.022 to 0.012, the risk index improves from 54.12 to 34.25, and energy consumption decreases from 110.5 kWh to 68.5 kWh. In the same way, increasing the fleet size from 10 to 50 vehicles lowers operational costs from 17,000 to 8,200, reduces delivery times from 0.025 to 0.010, and cuts energy consumption from 115.6 kWh to 67.3 kWh. These outputs highlight the model's ability to optimize logistics operations, reduce emissions, and enhance energy efficiency. The model also reveals trade-offs between objectives. For instance, increasing the fleet size improves energy efficiency and delivery times but may introduce challenges such as higher environmental impacts or risks, requiring careful balancing in decision-making. Sensitivity analyses emphasize the importance of managing resource allocation and scaling fleet size to achieve both operational and environmental goals.

By aligning numerical findings with LCA, this research underscores the potential of hybrid truck-drone systems to achieve long-term sustainability. The proposed multi-objective optimization framework demonstrates the potential of hybrid truck–drone delivery systems to simultaneously reduce costs, delivery times, energy consumption, and operational risk under various constraints. The SORA framework's incorporation of risk-aware planning enhances operational safety in unpredictable situations. To accommodate for variables like weather unpredictability, regulation changes, and demand spikes, future research may use scenario-based simulation or probabilistic approaches. To improve environmental resilience, future research may expand on this paradigm by integrating renewable energy sources and assessing cutting-edge technology like drone ports that run on solar power or battery recycling systems. Future research could conduct a comprehensive LCA in accordance with ISO 14040/44 standards, even if the current study focuses on energy consumption during the use-phase in accordance with life cycle thinking. Embodied emissions from the manufacture, maintenance, and final phases of the lives of vehicles and drones would fall under this category. Such an extension would enable a more comprehensive evaluation of the environmental sustainability of hybrid truck–drone logistics systems.

CRediT authorship contribution statement

Armin Mahmoodi: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation, Conceptualization, Formal analysis, Project administration, Resources, Software. **Seyed Mojtaba Sajadi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Funding acquisition, Data curation. **Jeremy Laliberte:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition. **Said M. Easa:** Funding acquisition, Supervision, Validation, Writing – review & editing.

Data availability

Data will be made available on request.

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