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A Fuzzy Multi-Objective Optimization Model for a Sustainable and Competitive UAV Delivery Network under Uncertainty

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Abstract- This paper presents a fuzzy multi-objective optimization model for the Green Location-Routing Problem (GLRP) in competitive UAV delivery networks. The model simultaneously optimizes total cost, carbon emissions, and service time while determining facility locations and UAV routes under realistic constraints: capacity, energy, and no-fly zones. To address inherent uncertainties in customer demand and travel times, we develop a fuzzy logic framework that generates robust Pareto-optimal solutions for different confidence levels (α). The resulting fuzzy model is solved using three meta-heuristic algorithms: NSGA-II, MOACO, and MOSA. Numerical results demonstrate that the proposed fuzzy approach yields a more practical and cost-effective design compared to deterministic models, effectively balancing economic and environmental objectives under uncertainty. This study offers logistics managers a robust decision-support tool for sustainable UAV network deployment.

Keywords: Unmanned Aerial Vehicle; Location-Routing; Multi-Objective; Competition; Fuzzy Optimization; Green Logistics.

I. INTRODUCTION

The logistics sector, central to the growing e-commerce industry, faces significant environmental challenges, with conventional transportation being a major contributor to global emissions (Park & Kim, 2018). The rapid increase in parcel volume necessitates innovative, sustainable solutions. Electric Unmanned Aerial Vehicles (UAVs) offer a promising path toward operational efficiency and ecological responsibility, promising expedited delivery and improved customer satisfaction (Dorling et al., 2016; Schermer et al., 2018). However, the full integration of UAVs is hampered by regulatory hurdles, battery life constraints, and the need to navigate complex operational environments (Farri & Winkenbach, 2022).

A critical challenge is the design of an efficient Green Location-Routing Problem (GLRP) network for UAVs, which involves strategically locating facilities and charging stations while simultaneously planning optimal flight routes. This problem is inherently multi-objective, balancing economic costs against environmental impacts such as CO_2 emissions (Coelho et al., 2017; Zhang et al., 2022). Existing literature has thoroughly explored the fundamentals of the Location-Routing Problem (LRP) for drones, addressing topics such as energy consumption models (Kim et al., 2019; Marinelli et al., 2018; Momeni et al., 2023) and general sustainability impacts (Coelho et al., 2017; Chyuan et al., 2019; Di Puglia Puglisi et al., 2020).

Nonetheless, a significant research gap persists. Most current optimization models are built upon deterministic assumptions (Kim et al., 2019; Chauhan et al., 2019). These models frequently prove inadequate for real-world scenarios where key operational parameters such as customer demand, travel times affected by localized weather, and energy consumption are inherently vague and imprecise (Figliozzi et al., 2020; Arafat & Sangman, 2022). This vagueness cannot be adequately captured by traditional stochastic approaches that require precise probability distributions.

This research addresses this critical gap by proposing a Fuzzy Multi-Objective Green Location-Routing Problem (FMOGLRP) model for UAV delivery systems operating under competitive conditions. The primary contributions of this work are:

1. **A Novel Fuzzy Mathematical Model:**
We develop a comprehensive multi-objective model that integrates facility location, UAV routing, and charging station placement under uncertainty, simultaneously optimizing for total profit, service time, and carbon emissions.
2. **Robust Uncertainty Handling:**
We employ a fuzzy set theory approach (Zadeh, 1965) to model the inherent ambiguity in customer demand and travel time, transforming the deterministic problem into a Fuzzy Multi-Objective Optimization Problem (FMOP) that generates robust solutions for various decision-maker confidence levels (α).
3. **A Comparative Meta-heuristic Analysis:**
We utilize and compare the performance of three advanced meta-heuristic algorithms a modified Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002), Multi-Objective Ant Colony Optimization (MOACO) (Dorigo et al., 1996), and Multi-Objective Simulated Annealing (MOSA) (Kirkpatrick et al., 1983) to solve the complex fuzzy model efficiently.
4. **Practical Validation:**
Through numerical experiments and a case study, we demonstrate that our fuzzy-based network design provides more practical and resilient solutions compared to traditional deterministic methods when faced with real-world uncertainties.

The remainder of this paper is structured as follows: Section 2 reviews existing work on GLRP, sustainability, and uncertainty modeling. Section 3 presents the problem definition and the crisp mathematical formulation. Section 4 introduces the fuzzy uncertainty framework and the solution methodology. Section 5 discusses the computational results and sensitivity analysis. Finally, Section 6 concludes the paper with managerial insights and future research directions.

II. LITERATURE REVIEW

This section reviews key research streams relevant to our study, including facility location and network design, routing strategies, green logistics, energy consumption, and operational constraints such as no-fly zones and flight safety, culminating in the identification of the research gap.

Facility Location and Network Design
Research in this area focuses on the strategic placement of infrastructure. Kim et al. (2017) proposed a two-phase method for distributing medical supplies via drones, while Sheverini et al. (2019) minimized costs for launch and charging stations. Kim et al. (2019) developed a stochastic model for UAV deployment in emergencies, and Chauhan et al. (2019) worked on maximizing coverage without considering battery recharging. A notable gap exists in the simultaneous optimization of facility locations and charging stations for drone delivery networks.

Routing Strategies for UAVs
The Vehicle Routing Problem with Drones (VRPD) is a complex and active area. Liu et al. (2017) examined coordinated routing for a ground vehicle and a UAV. Subsequent studies improved delivery routes for truck-drone teams (Sik et al., 2018; Amro et al., 2019; Wang et al., 2019). Research has evolved to include time windows (Li et al., 2020), energy reduction (Amorosi et al., 2020), and synchronization of drone and truck operations (Das et al., 2020). Recent works continue to optimize delivery times and energy use (Momeni et al., 2023; Yuan, 2023; Farrag et al., 2024).

Green Routing and Environmental Sustainability
Incorporating environmental objectives is crucial. Coelho et al. (2017) introduced a green routing problem using multiple UAVs and charging stations. Chiang et al. (2019) and Di Puglia Pugliese et al. (2020) quantified the CO_2 emissions of drones versus traditional vehicles. Zhang et al. (2022) developed a multi-objective model to reduce energy consumption in combined drone-vehicle delivery systems, highlighting a growing emphasis on eco-friendly logistics.

Energy Consumption and Operational Limitations
UAV performance is inherently tied to energy constraints. Liang et al. (2019) developed path selection methods considering energy limits, while Okansi et al. (2021) and Kirchstein (2021) created

models to minimize energy-related costs. Studies note that drones can consume more energy than ground vehicles, presenting a key research challenge (Colyasar et al., 2023). Recent research explores hybrid systems and 3D scheduling to address these issues (Ruifeng et al., 2024; Lin et al., 2025).

No-Fly Zones and Flight Safety
Adherence to airspace regulations is paramount. Zhang and Duan (2015) optimized UAV path planning in 3D environments with no-fly zones. Gao et al. (2019) and Huang et al. (2020) designed trajectories for UAVs to avoid prohibited areas while maintaining communication. Safety is also addressed through location-routing algorithms for supporting infrastructure (Macias et al., 2018) and spatial routing in urban areas (Jing et al., 2020).

Identification of the Research Gap
While the reviewed literature provides a strong foundation in Location-Routing, green objectives, and safety constraints, a critical gap remains. Most established LRP and GLRP models rely on deterministic assumptions, failing to robustly account for inherent operational vagueness, such as fluctuating demand or ambiguous travel parameters. Furthermore, the simultaneous incorporation of multi-objective optimization (cost vs. environmental impact) within a competitive market environment under an explicit Fuzzy Uncertainty framework has not been sufficiently addressed. This research directly targets this deficiency by formulating a Fuzzy Multi-Objective GLRP (FMOGLRP) and employing a modified NSGA-II algorithm to derive robust solutions, thereby extending the state-of-the-art beyond purely deterministic approaches.

Table 1. The summarized literature review and research position

Relationship between authors and the implemented constraints and main titles

Authors	Locati	Routi	Gree	Functional		
				Battery/f	No	Flight
Kim et al.	*	*				
Sheverini et	*	*		*		
Kim et al.	*			*		
Chauhan et al.	*	*		*		
kim et al. (	*	*		*		
Ilkhanizadeh	*	*				
Huang et al.	*	*		*		
Liu et al.		*		*		
Sik et al.		*				
Amro et al.		*				
Young et al.		*		*	*	
Wang et al.		*		*		
Li et al. (2020)		*				
Amorosi et al.		*		*		
Das et al.		*				
PanelLuigi et		*				
Baloch et al.	*	*				
Sajid et al.		*				*
Mao et Al.		*		*		
Momeni		*		*		*
Yuan (2023)		*				
Raivi et al.		*		*		
Nishira et al.		*				
Zieher et al.	*	*				
Lan et al.		*		*		
Farrag et al.		*		*		
Mulumba et		*		*		
Ghonim et al.		*		*		
Coelho et al.		*	*			
Chiang et al.		*	*			
Dipolia et al.		*	*			
Zhang et al.			*	*	*	
Lamb et al.		*	*			
Almodather		*	*			
Liang et al.		*		*		
Okanci et al.				*		*
Kirschestin				*		
Kyriakakis et				*		
Ahmadi javid		*		*		
Cokyasar et		*		*		
Ruifeng et al.		*		*		
Lin et al.		*		*		
Mokhtari		*		*		
Zhang et al.		*			*	
GAO et al.		*			*	
Huang et al.		*		*	*	
Macias et al.	*	*				*
Jing et al.		*				*
Arafat et al.		*		*		*

Saunders et		*				*
Current	*	*	*	*	*	*

III. PROBLEM DEFINITION AND FORMULATION

This section presents the crisp (deterministic) formulation of the Green Location-Routing Problem (GLRP) for a UAV-based delivery network operating in a competitive environment. The model is initially developed as a Multi-Objective Mixed-Integer Programming (MOMIP) model.

Problem Description and Framework

The study develops a mathematical model to design a sustainable UAV delivery network. The primary objectives are to maximize total profit, minimize total drone service time, and reduce carbon emissions associated with the distribution network. The model simultaneously optimizes the selection of facility locations and charging stations while designing efficient UAV routes. A schematic representation of this integrated network, encompassing facilities, customers, charging stations, and potential UAV routes, is provided in **Fig. 1.**

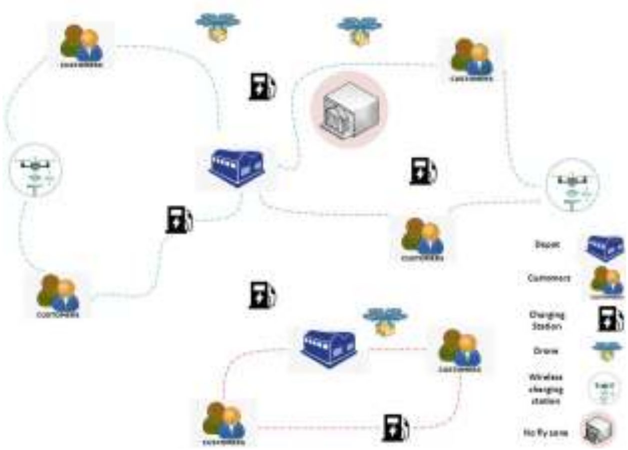

Figure 1.A graphic illustration of the examined problem

The feasibility of integrating UAV package delivery within a competitive retail environment is examined, considering customer demands and critical operational constraints such as package weight, payload capacity, battery life, and landing site availability. A key operational challenge involves navigating no-fly zones and maintaining strict flight safety standards, which are conceptually illustrated in **Fig. 2**. Crucially, real-world operational parameters including fluctuating customer demand, travel times influenced by weather, and battery performance are subject to inherent uncertainty. Therefore, to enhance robustness beyond traditional deterministic models, this research will later extend the formulation (in Section 4) to explicitly address these ambiguities by incorporating a Fuzzy Uncertainty Approach. The model must satisfy multi-objective constraints related to service delivery, energy management, No-Fly Zone (NFZ) compliance, and flight safety, all within a competitive landscape where customer choice is influenced by proximity and service availability.

Figure 2.A graphic illustration of No-Fly Zone

Model Assumptions and Indices

The main assumptions of the model are as follows:

- The recharging process of a UAV is not affected by other UAVs at the station.
- Service times for recharging or loading remain constant.
- Flight conditions are stable, with pre-defined no-fly zones.
- UAVs have fixed load and battery capacities.
- Customer locations and potential charging station locations are fixed and known in advance.

The indices, sets, parameters, and decision variables used in the model are defined below.

Explanation	Index
Index of candidate areas for	L
Index of customer areas	I

Index of potential locations to	J
Index of packages that can be	P
Index of drones	K
No-fly zone index	Z'
Retailer Service Index	S
	Sets
A set of retailer services that S_{new}	S
is the service in the store	S_o
The set of candidate areas for	L
Set of customer areas $I = \{1, \dots, n\}$	I
Set of potential locations to	J
A set of packages $P = \{\bullet, 1\}$	P
Set of all nodes (reopened facility,	TN
Collection of charging centers	CH
Set of drones $K = \{1, \dots, k\}$	K
A set of no-fly zones	NZ
	parameters
It is equal to 1 if service $s \in S$ can	a_{sp}
It is equal to 1 if region i is	r_{ils}
The number of drones in the	N_d
The distance between node i and	d_{ijk}
Available capacity of K-th UAV	C_k
Upper limit of portable weight	UL_k
package weight p	W_p
UAV charging capacity (kw)	FC
fuel consumption rate depending	ρ
Fuel consumption rate depending	θ
The time to travel the path (i,j)	t_{ijk}
It is equal to 1 if the k drone is	RA_k
The demand of the i-th node (the	D'_i
Maximum length of tours	$Tmax$
Service time at i-th node for k-th	TS_{ik}
Number of base charging stations	N_b
Number of wireless charging	N_w
Large positive number	M
Amount of Co_2 emitted in electric	PGF
The average energy requirement	AER_k
The air speed of the k-th UAV	$SP_{i,j,k}$
The flight path angle of the k-th	$\gamma_{i,j,k}$
The head angle (upper angle) of	$\vartheta_{i,j,k}$
Horizontal safety distance	R_{xy}
Vertical safety distance	R_z
Start time of no-fly zone Z'	$St_{Z'}$
end time of the no-fly zone Z'	$et_{Z'}$
The cost of reopening the	C_l

The cost of providing S services in	C_s
profit margin	α
value of package p	π_p
Cost of delivery of each unit to	Cu_{ils}
Delivery cost for service $s \in S$	Cd_s
Cost per unit of fuel ($\frac{\$}{KW}$)	Co
The fixed cost of using a drone	Fk
Fixed cost per refueling	Fs
The cost of re-opening the base	Cb_i
The cost of reopening a wireless	Cw_i
Maximum store size in region $i \in$	N_{ip}
Service delivery time $s \in S$	DT_s
Travel time to the nearest store	TT_i
Cost of traveling to the nearest	TC_i
The inherent attractiveness of	βo_s
Delivery time sensitivity	βdt
Delivery cost sensitivity	βdc
Travel time sensitivity	βtt
Travel cost sensitivity	βtc
Store size elasticity with respect	λ
Additional deviation time from	$Ot_{i,j,z'}$
Penalty for speeding up the i-th	Ce_{ik}
Penalty for the delay of the i-th	Cl_{ik}
Start time of the time window	E_i
End time of the time window	L_i
	Decision
The amount of fuel k-th drone has	ϕ_{ik}
The amount of fuel k-th drone	q_{jk}
The time of the arrival of k-th	$tarr_{i,k}$
Cartesian coordinates	$\chi'_{i,j,k}$
Cartesian coordinates	$y'_{i,j,k}$
Cartesian coordinates	$Z'_{i,j,k}$
It is equal to 1 if the facilitation $l \in$	F_l
It is equal to 1 if the service $s \in S$	χ_{ls}
It is equal to 1 if region $i \in I$ is	y_{ils}
Performance function of area $i \in$	u_{ip}
Request received by service $s \in S$	D_{isp}
Share of D_{isp} served by	d_{ilsp}
The value of the objective	Z
It is equal to 1 if the k-th UAV	χ_{ijk}
The amount of cargo carried by	W_{ijk}
It is equal to 1 if the base charge	Zb_i
It is equal to 1 if the wireless	Zw_i
It is equal to 1 if the base charging	$Ub_{i,k}$

It is equal to 1 if the wireless	$Uw_{i,k}$
It is equal to 1 if the UAV's arrival	$Ze_{i,Z'}$
It is equal to 1 if the UAV's arrival	$Zs_{i,Z'}$

Objective Functions:

1. **Maximize Total Profit (ZP_1):**

This function aggregates revenue from delivered packages, subtracting costs associated with facility reopening, service provision, energy consumption, drone usage, fixed charging costs, and penalties for early or late deliveries.

$$\max ZP_1 = \sum_{i\in I}\sum_{l\in L}\sum_{s\in S}\sum_{p\in P}\left(\alpha\pi_p + Cd_s - Cu_{ils}\right)d_{ilsp} - \sum_{l\in L}\sum_{s\in S} C_s\chi_{ls} - \sum_{l\in L} C_l \cdot F_l - \sum_{i\in TN}\sum_{j\in TN}\sum_{k\in K} CO \cdot d_{ijk}\left(\rho \cdot \chi_{ijk} + \theta \cdot W_{ijk}\right) - \sum_{l\in TN}\sum_{i\in TN/\{l\}}\sum_{k\in K} Fk \cdot \chi_{lik} - \sum_{i\in TN}\sum_{j\in TN}\sum_{k\in K} Fs \cdot \chi_{ijk} - \sum_{i\in TN} Cb_i \cdot Zb_i - \sum_{i\in TN} Cw_i \cdot Zw_i - \sum_{i\in TN}\sum_{j\in TN}\sum_{k\in K} Fk.\,(d_{ijk} \cdot \chi_{ijk}) - \sum_{i\in TN}\sum_{k\in K} Ce_{ik}.\,(E_i - tarr_{ik}) - \sum_{i\in TN}\sum_{k\in K} Cl_{ik}(\,tarr_{ik} - L_i) \qquad (1)$$

2. **Minimize Total Service Time (ZP_2):**

This function represents the cumulative flight time of all drones.

$$\min ZP_2 = \sum_{i\in TN}\sum_{j\in TN}\sum_{k\in K} t_{ijk} \cdot \chi_{ijk} \qquad (2)$$

3. **Minimize Total Carbon Emissions (ZP_3):**

This function calculates the total CO2 emissions based on the energy consumption of the UAV fleet.

$$\min ZP_3 = \sum_{i\in TN}\sum_{j\in TN}\sum_{k\in K} PGF \cdot AER_k \cdot d_{ijk} \cdot \chi_{ijk} \qquad (3)$$

Subject to:

The model is subject to a comprehensive set of constraints, including but not limited to:

Service and Allocation Constraints (Eqs. 4-10):

Ensure correct customer-to-facility and service-to-facility assignments.

$$\sum_{l\in L} y_{ils} \le 1 \qquad \forall i \in I\ , s \in S \qquad (4)$$

$$y_{ils} \le r_{ils} \cdot \chi_{ls} \qquad \forall i \in I\,, l \in L\ , s \in S \qquad (5)$$

$$\chi_{ls} \le F_l \qquad \forall l \in L\ , s \in S \qquad (6)$$

$$\sum_{l\in L} F_l \ge 1 \qquad (7)$$

$$d_{ilsp} \le M \cdot y_{ils} \forall i \in I\,, l \in L\ , s \in S, p \in P \qquad (8)$$

$$\sum_{l\in L} d_{ilsp} \le D_{isp} \forall i \in I\ \ , s \in S, p \in P \qquad (9)$$

$$\sum_{i\in L}\sum_{j\in TN} \chi_{ijk} \le \sum_{i\in L} r_{ils} \cdot \chi_{ls} \qquad \forall k \in K\,, l \in L\ , s \in S \qquad (10)$$

Demand Capture Constraints (Eqs. 11-12):

Model customer choice behavior and calculate the captured demand based on utility and proximity.

$$U_{ip} = \sum_{s\in S}((\sum_{l\in L} a_{sp} \cdot y_{ils}) \cdot \exp(\beta O_s - \beta dt \cdot DT_s - \beta dc \cdot Cd_s) + \exp\left(\beta O_{s_{new+l}} - \beta tt \cdot TT_i - \beta tc \cdot TC_i\right) \qquad (11)$$

$$D_{isp} = \frac{N_{ip}\left(1 - \exp(1 - \lambda U_{ip})\right)\left(\sum_{l\in L} a_{sp} \cdot y_{ils}\right) \cdot \exp(\beta O_s - \beta dt \cdot DT_s - \beta dc \cdot C}{U_{ip}}$$

Routing and Flow Constraints (Eqs. 13-18):

Guarantee the continuity and feasibility of UAV routes (e.g., each customer is visited once, flow conservation).

$$\sum_{l\in L}\sum_{i\in TN|\{l\}} \chi_{lik} = 1 \qquad \forall k \in K \qquad (13)$$

$$\sum_{i\in L}\sum_{j\in L} \chi_{ijk} = 0 \qquad \forall k \in K \qquad (14)$$

$$\sum_{k\in K}\sum_{j\in TN} \chi_{ijk} = 1 \qquad \forall i \in TN \qquad (15)$$

$$\sum_{k\in K}\sum_{j\in TN} \chi_{ijk} \le 1 \qquad \forall i \in CH \qquad (16)$$

$$\sum_{i\in TN} \chi_{jik} - \sum_{i\in TN} \chi_{ijk} = 0 \qquad \forall j \in TN, k \in K \qquad (17)$$

$$\sum_{k\in K}\sum_{j\in TN} W_{jik} = D'_i + \sum_{k\in K}\sum_{j\in TN} W_{ijk} \qquad \forall i \in TN|\{l\} \qquad (18)$$

Capacity and Load Constraints (Eq. 19):

Ensure the cargo carried on each route does not exceed the UAV's capacity.

$$W_{ijk} \le C_k \cdot \chi_{ijk} \qquad \forall i, j \in TN, k \in K \qquad (19)$$

Energy Management Constraints (Eqs. 20-25):

Track and manage UAV fuel levels, ensuring they have sufficient charge to reach the next node and are refueled at stations.

$$d_{ijk}(\rho \cdot \chi_{ijk} + \theta \cdot W_{ijk}) - FC(1-\chi_{ijk}) \le \phi_{ik} - q_{jk} \quad \forall i \in TN, j \in CH, k \in K \quad (20)$$

$$\phi_{ik} - q_{jk} \le d_{ijk}(\rho \cdot \chi_{ijk} + \theta \cdot W_{ijk}) + FC(1-\chi_{ijk}) \quad \forall i \in TN, j \in CH, k \in K \quad (21)$$

$$d_{ijk}(\rho \cdot \chi_{ijk} + \theta \cdot W_{ijk}) - FC(1-\chi_{ijk}) \le \phi_{ik} - \phi_{jk} \quad \forall i \in TN, j \in CH, k \in K \quad (22)$$

$$\phi_{ik} - \phi_{jk} \le d_{ijk}(\rho \cdot \chi_{ijk} + \theta \cdot W_{ijk}) + FC(1-\chi_{ijk}) \quad \forall i \in TN, j \in CH, k \in K \quad (23)$$

$$\phi_{ik} = FC \quad \forall i \in \{L\} \cup CH, k \in K \quad (24)$$

$$\phi_{ik} \ge d_{ijk}(\rho \cdot \chi_{ijk}) \quad \forall i \in TN \cup CH, \forall j \in TN, k \in K \quad (25)$$

$$\sum_{i \in TN|\{l\}} \chi_{lik} \ge 1 \quad \forall\, k \in K, l \in L \quad (26)$$

$$\sum_{i \in TN|\{l\}} \chi_{ilk} \le N_d \quad \forall\, k \in K, l \in L \quad (27)$$

Time Window Constraints (Eqs. 28-31):

Enforce delivery within specified customer time windows, including penalties for early or late arrivals.

$$tarr_{jk} \le \left(1 - \sum_{i \in TN} \chi_{ijk}\right).M + L_j \quad \forall j \in TN|\{l\}, k \in K \quad (28)$$

$$tarr_{jk} \ge \left(\sum_{i \in TN} \chi_{ijk} - 1\right).M + E_j \quad \forall j \in TN|\{l\}, k \in K \quad (29)$$

$$tarr_{jk} \ge tarr_{ik} + TS_{ik} \cdot \chi_{ijk} + t_{ijk} + (\chi_{ijk} - 1).M \quad \forall i \in TN, j \in TN|\{l\}, k \in K \quad (30)$$

$$\sum_{i \in L} \sum_{j \in TN} \chi_{ijk} . TS_{ik} + \sum_{i \in L} \sum_{j \in TN} \chi_{ijk} . t_{ijk} \le Tmax \quad \forall k \in K \quad (31)$$

Charging Station Constraints (Eqs. 32-39):

Limit the number and manage the operation of base and wireless charging stations.

$$\sum_{i \in CH} Zb_i \le N_b \quad (32)$$

$$\sum_{i \in CH} Zw_i \le N_w \quad (33)$$

$$\sum_{i \in CH} Zb_i \ge 1 \quad (34)$$

$$\sum_{i \in CH} Zw_i \ge 1 \quad (35)$$

$$Ub_{ik} \le Zb_i \quad \forall i \in CH, k \in K \quad (36)$$

$$Uw_{ik} \le Zw_i \quad \forall i \in CH, k \in K \quad (37)$$

$$\sum_{i \in TN} Ub_{ik} \le \sum_{i \in TN} y_{ils} \quad \forall k \in K, l \in L, s \in S \quad (38)$$

$$\sum_{i \in TN} Uw_{ik} \le \sum_{i \in TN} y_{ils} \quad \forall k \in K, l \in L, s \in S \quad (39)$$

$$\sum_{i \in TN} \sum_{\substack{j \in TN \\ i \ne j}} t_{ijk} \le Tmax \quad \forall k \in K \quad (40)$$

$$\sum_{i \in TN} \sum_{\substack{j \in TN \\ i \ne j}} D_{isp} \cdot \chi_{ijk}. W_p \le UL_k \quad \forall s \in S, k \in K, p \in P \quad (41)$$

$$\sum_{i \in CH} Ub_{ik} . RA_k \ge 1 \quad \forall k \in K \quad (42)$$

$$\sum_{i \in CH} Uw_{ik} . (1 - RA_k) \ge 1 \quad \forall k \in K \quad (43)$$

No-Fly Zone Constraints (Eqs. 44-49):

Ensure UAVs avoid restricted airspace within specified time intervals. The decision-making process for deviation around a no-fly zone is detailed in **Fig. 15**.

$$tarr_{jk} \ge tarr_{ik} + t_{ijk} + \sum_{Z' \in NZ} Ot_{i,j,z'} (Ze_{i,Z'} - Zs_{j,Z'}) - M[1 - \chi_{ijk}] \forall i \in I, j \in TN, i \ne j, k \in K \quad (44)$$

$$tarr_{jk} \le tarr_{ik} + t_{ijk} + \sum_{Z' \in NZ} Ot_{i,j,z'} (Ze_{i,Z'} - Zs_{j,Z'}) + M[1 - \chi_{ijk}] \forall i \in I, j \in TN, i \ne j, k \in K \quad (45)$$

$$tarr_{ik} \ge St_{Z'} - M \cdot Zs_{i,Z'} \quad \forall i \in TN, Z' \in NZ \quad (46)$$

$$tarr_{ik} \le St_{Z'} + M(1 - Zs_{i,Z'}) \quad \forall i \in TN, Z' \in NZ \quad (47)$$

$$tarr_{ik} \ge ET_{Z'} - M \cdot Ze_{i,Z'} \quad \forall i \in TN, Z' \in NZ \quad (48)$$

$$tarr_{ik} \leq ET_{Z'} + M \cdot (1 - Ze_{i,Z'}) \qquad \forall i \in TN, Z' \in NZ \qquad (49)$$

Flight Safety Constraints (Eqs. 50-54):
Maintain safe horizontal and vertical distances between UAVs during flight.

$$\chi'_{i,j,k} = \chi'_{l,l,k} + t_{lik} \cdot SP_{l,i,k} \cdot \cos(\gamma_{l,i,k}) \cos(\vartheta_{l,i,k}) \,.\, \chi_{ijk} \qquad \forall i,j \in TN, k \in K \qquad (50)$$

$$y'_{i,j,k} = y'_{l,l,k} + t_{lik} \cdot SP_{l,i,k} \cdot \cos(\gamma_{l,i,k}) \sin(\vartheta_{l,i,k}) \,.\, \chi_{ijk} \qquad \forall i,j \in TN, k \in K \qquad (51)$$

$$Z'_{i,j,k} = Z'_{l,l,k} + t_{lik} \cdot SP_{l,i,k} \cdot \sin(\gamma_{l,i,k}) . \chi_{ijk} \qquad \forall i,j \in TN, k \in K \qquad (52)$$

$$(\chi'_{l,l,k} - \chi'_{i,j,k})^2 + (y'_{l,l,k} - y'_{i,j,k})^2 \geq Rxy^2 \qquad \forall i,j,i',j' \in TN, k \in K \qquad (53)$$

$$(Z'_{l,l,k} - Z'_{i,j,k})^2 \geq Rz^2 \forall i,j,i',j' \in TN, k \in K \qquad (54)$$

The decision logic for UAV deviation when encountering a no-fly zone is visually summarized in Fig. 3, which illustrates the six possible temporal relationships between UAV arrival times and the no-fly zone activation period.

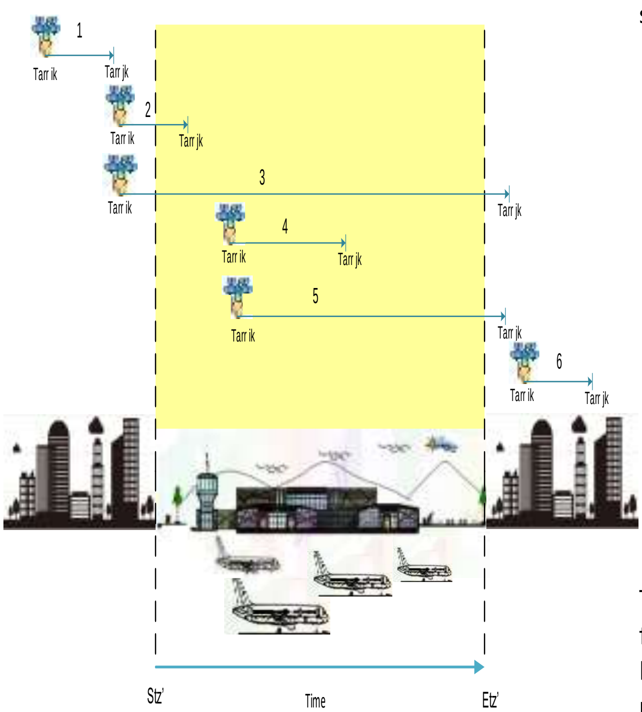

Fig. 3. Deviation decision process according to the time of the no-fly zone

The corresponding binary variable combinations and deviation decisions are detailed in Table 2 until 4.

Table 2. Deviation decision process according to the time of the no-fly zone

If	Then $Ze_{i,Z'}$	If	Then $Zs_{j,Z'}$
$tarr_{i,k} < et_{Z'}$	1	$tarr_{i,k} < St_{Z'}$	1
$tarr_{i,k} > et_{Z'}$	0	$tarr_{i,k} > St_{Z'}$	0

Table 3. Deviation decision results according to the time of the no-fly zone

Item	$Ze_{i,Z'}$	$Zs_{j,Z'}$	$Ze_{i,Z'}$-$Zs_{j,Z'}$	Deviation
1	1	1	0	No
2	1	0	1	Yes
3	1	0	1	Yes
4	1	0	1	Yes
5	1	0	1	Yes
6	0	0	0	No

The analysis involved binary variables and drone flight paths in no-fly zones, with customer areas showing adherence to the decision process. Various scenarios validated the mathematical model. Three solution approaches were compared based on speed, optimality, and answer quality.

Table 4. Specifications of designed problems

Specifications	Little	medium	big
Nl	4	15	100
No	5	20	50
Nj	5	20	30
n.p	3	18	25
Nk	2	10	30
Ns	4	16	30
hnf	4	15	25

IV. SOLUTION METHODOLOGY FOR THE FMOP

This section presents the integrated solution framework for the Fuzzy Multi-Objective Green Location-Routing Problem (FMOGLRP). The methodology consists of two core components: (1) a fuzzy uncertainty modeling approach that transforms imprecise parameters into α-level dependent crisp intervals, and (2) a modified multi-objective evolutionary algorithm specifically adapted to solve the resulting robust optimization model. The overall solution framework is depicted in Figure X.

Fuzzy Uncertainty Modeling Framework

- **Justification for Fuzzy Set Theory**

Real-world UAV delivery operations are characterized by epistemic uncertainties arising from volatile environmental conditions and incomplete information. Key uncertain parameters include:

- **Demand fluctuation ($\widetilde{D}_i$):**

Actual customer orders often deviate from forecasts due to dynamic market conditions.

- **Travel time variability ($\widetilde{T}_{ij}^{k}$):**

Flight durations are highly sensitive to wind speed, air traffic, and localized weather patterns.

- **Energy consumption uncertainty ($\widetilde{E}_{req}^{k}$):**

Battery drain fluctuates with payload weight, temperature, and flight altitude.

Unlike stochastic approaches requiring extensive historical data, Fuzzy Set Theory (Zadeh, 1965) provides a mathematically rigorous framework for modeling this type of subjective, knowledge-based uncertainty through membership functions that quantify the degree of truth.

Formal Definition of Fuzzy Parameters

Uncertain parameters are modeled as fuzzy numbers with explicit membership functions. For computational tractability and interpretability, we employ:

Triangular Fuzzy Number for Demand ($\widetilde{D}_i$):

$$\mu_{\widetilde{D}_i}(d) = \begin{cases} \frac{d-D_i^L}{D_i^M-D_i^L} & \text{if } D_i^L \le d \le D_i^M \\ \frac{D_i^U-d}{D_i^U-D_i^M} & \text{if } D_i^M \le d \le D_i^U \\ 0 & \text{etc} \end{cases}$$

(55)

Trapezoidal Fuzzy Number for Travel Time ($\widetilde{T}_{ij}^{k}$):

$$\mu_{\widetilde{T}_{ij}^k}(t) = \begin{cases} 0 & \text{if } t < T_{ij}^{k,L} \\ \frac{t-T_{ij}^{k,L}}{T_{ij}^{k,M}-T_{ij}^{k,L}} & \text{if } T_{ij}^{k,L} \le t \le T_{ij}^{k,M} \\ 1 & \text{if } T_{ij}^{k,M} \le t \le T_{ij}^{k,U} \\ \frac{T_{ij}^{k,\acute{U}}-t}{T_{ij}^{k,\acute{U}}-T_{ij}^{k,U}} & \text{if } t > T_{ij}^{k,\acute{U}} \end{cases}$$

(56)

Where superscripts L, M, U denote lower, most likely, and upper bounds respectively.

The corresponding membership functions are illustrated in **Fig.4** Triangular and trapezoidal shapes offer a balance between representational flexibility and computational efficiency.

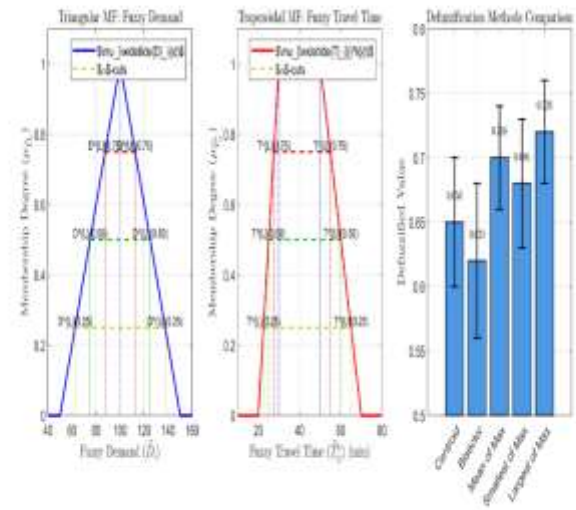

Figure. 4.FuzzyMembershipFunctions

As demonstrated in Fig.4, the centroid defuzzification method (panel c) yields the most stable solutions, justifying its adoption in our solution methodology. This mathematical formalization extends beyond conventional stochastic approaches by explicitly incorporating decision-maker risk preferences through the α parameter.

α-Cut Based Transformation to Crisp Equivalents

The fuzzy model is transformed into a solvable deterministic counterpart using the α-cut technique. For a specified confidence level α∈[0,1], the α-cut intervals are:

For triangular fuzzy demand $\widetilde{D}_i=(D_i^L, D_i^M, D_i^U)$:

$\widetilde{D}_i(\alpha)=[\underline{D}_i(\alpha),\overline{D}_i(\alpha)]=[D_i^L+\alpha(D_i^M-D_i^L),\ D_i^U-\alpha(D_i^U-D_i^M)]$

(57)

For trapezoidal fuzzy travel time $\widetilde{T}_{ij}^{k}=(T_{i,j}^{k,l}, T_{i,j}^{k,M1}, T_{i,j}^{k,M2}, T_{i,j}^{k,U})$:

$\widetilde{T}_{ij}^{k}(\alpha)=[\underline{T}_{i,j}^{k}(\alpha),\overline{T}_{i,j}^{k}(\alpha)]=[T_{i,j}^{k,l}+\alpha(T_{i,j}^{k,M1}-T_{i,j}^{k,l}),\ T_{i,j}^{k,U}-\alpha(T_{i,j}^{k,U}-T_{i,j}^{k,M2})]$ (58)

Critical Implementation Note: The transformation of constraints must account for the type of uncertainty:

For demand fulfillment constraints, we use the upper bound $\overline{D}_i$ (α) to ensure sufficient capacity
For travel time constraints, we use the upper bound $\overline{T}_{i,j}^{k}$(α) to guarantee timely delivery
For budget constraints, we use the lower bound of revenue parameters

Reformulated α-Robust Multi-Objective Model
The original FMOGLRP transforms into an α-parametrized crisp model:
Objectives:
max Z_1(α)=Total
Profit (evaluated using pessimistic parameter bound s)
min Z_2(α)= Total
Service time (evaluated using $\overline{T}_{i,j}^{k}$(α))
min Z_3(α)= Total Co2
Emissions (evaluated using conservative energy esti mates)
Subject to:

- **Flow conservation constraints (unchanged)**
- **Robust demand fulfillment:**
  $\sum_{l\in L} d_{ilsp} \geq \overline{D}_i$ (α) ·(1−si)
- **Robust capacity constraints:**
  $\sum_{i\in I} \overline{D}_i$ (α)· $y_{ils} \leq C_l$
- **Robust time windows:**

$tar_{jk} \leq tar_{ik} + \overline{T}_{i,j}^{k}(α) + M(1 - x_{ijk})$

- All other operational constraints from Section 3

Modified NSGA-II for Fuzzy Multi-Objective Optimization
To efficiently solve the α-robust model, the standard NSGA-II (Deb et al., 2002) is extensively modified to operate in the fuzzy domain.

Solution Representation (Chromosome Encoding)
A structured matrix-based encoding scheme is developed to represent all decision variables compactly. For an instance with M facilities, N customers, S services, and K drones, the chromosome is defined as:
Z=[OF / Y / C / P / W]
where:

- **OF**: Binary vector (M×1) for facility opening status
- **Y**: Binary matrix (M×N) for customer-facility assignment
- **C**: Binary matrix (M×S) for service-facility assignment
- **P**: Set of binary matrices encoding drone flight paths
- **W**: Numerical vector for payload on each route segment

Fuzzy Dominance and Evaluation
The key adaptation lies in the fitness evaluation and comparison mechanisms:
• **Fuzzy Objective Evaluation:**
Each solution is evaluated using the α-cut parameter values, yielding objective vectors that represent performance under the specified uncertainty level.
• **Fuzzy Pareto Dominance:**
Solution x dominates solution y (x>fuzzy y) if:
○ f_m(x,α)≤ f_m(y,α) for all minimization objectives m
○ ∃j: f_j(x,α)< f_j(y,α)
where comparisons use the conservative α-cut bounds.

Algorithmic Procedure
The step-by-step procedure of the modified NSGA-II is summarized in Table 5 and proceeds as follows:
1- Initialization: Generate initial population P_0 of size N with random feasible solutions.
2- Main Loop: For generation t=1 to T_{max}:
a. **Genetic Operations:** Apply tournament selection, simulated binary crossover, and polynomial mutation to create offspring population Q_t .
b. **Population Merging:** Combine parent and offspring: $R_t = P_t \cup Q_t$.
c. **Fuzzy Evaluation:** Evaluate all solutions in R_t using α-cut parameter values.
d. **Fuzzy Non-dominated Sorting:** Sort R_t into non-domination fronts $F_1, F_2, \ldots$ using fuzzy dominance criteria.
e. **Next Population Selection:** Fill P_{t+1} with solutions from the best fronts, using fuzzy crowding distance for diversity preservation when necessary.
3- Termination: Return the non-dominated set from the final population as the α-robust Pareto front.

Table 5. Step-by-step procedure of the modified NSGA-II algorithm for fuzzy optimization

Step	Process	Description	Key Features / Modifications
1	Initialization	Generate initial random population P_0 of size N	Random feasible solutions
2	Main Loop	For generation t = 1 to T	Maximum number of generations
3	Genetic Operators	Apply crossover and mutation to P_t	Creates offspring population Q_t
4	Population Merging	Combine parent and offspring: $R_t = P_t \cup Q_t$	Population size: 2N
5	Fuzzy Evaluation	Evaluate each solution using α-cut bounds	Primary modification: Objectives and constraints evaluated under uncertainty using $\widetilde{D}_i(\alpha)$ and $\widetilde{T}_{ij}^{k}(\alpha)$
6	Fuzzy Non-dominated Sorting	Sort R_t into non-dominated fronts F_1, F_2, …	Primary modification: Dominance determined in fuzzy objective space using α-level comparisons
7	Next Population Initialization	Set $P_{t+1} = \varnothing$ and i = 1	Prepares for elitist selection
8	Front Selection	While $\lvert P_{\{t+1\}} \rvert + \lvert F_i \rvert \leq N$: Add entire fro	Preserves best non-dominated solutions
9	Crowding Distance Calculation	Calculate crowding distance for solutions in F_i	Maintains diversity in objective space
10	Diversity-based Selection	Sort F_i by crowding distance; select most diverse solutions to fill remaining slots in P_{t+1}	Ensures spread across Pareto front
11	Termination Check	If t = T: Stop; Else: t = t + 1, go to Step 3	Convergence criterion
12	Output	Extract non-dominated solutions	

Step	Process	Description	Key Features / Modifications
		from final population P_T	

Parameter Settings

The algorithm parameters were calibrated through extensive preliminary experiments:

- Population size: N=100
- Maximum generations: T_{max}=300
- Crossover probability: P_c =0.9
- Mutation probability: P_m=0.1
- Distribution indices for SBX and polynomial mutation: η_c =20, η_m=20

Benchmark Algorithms

For comparative analysis, two additional multi-objective metaheuristics were implemented:

1. **Multi-Objective Ant Colony Optimization (MOACO):**
Adapted with pheromone updates based on fuzzy dominance rankings.
2. **Multi-Objective Simulated Annealing (MOSA):**
Modified with acceptance criteria considering α-level objective values.

Both algorithms were implemented with comparable computational effort (population size and function evaluations) to ensure fair comparison.

Overall Solution Framework

The complete solution process involves an outer loop over α values and an inner optimization loop:

1. **Select α Levels:** Define discrete set α∈{0.0,0.25,0.5,0.75,1.0}
2. **For each α:**
a. Calculate α-cut parameter bounds using Eqs. (57)-(58)
b. Solve the resulting crisp multi-objective model using modified NSGA-II
c. Store the obtained Pareto front as the α-robust solution set

Aggregate Results: Combine all α-level Pareto fronts to form the complete fuzzy trade-off surface.

This integrated approach enables decision-makers to select solutions based on both performance metrics and desired robustness levels.

5. Computational Experiments and Results

5.1. Experimental Setup and Benchmark Instances

To validate the proposed FMOGLRP model and solution approach, extensive computational experiments were conducted. The algorithms were implemented in MATLAB R2024b and executed on a workstation equipped with an Intel® Core™ i7-12700K processor and 32 GB of RAM. Three test sets with varying scales were utilized, as detailed in Table 6.

The fuzzy parameters were mathematically defined as triangular and trapezoidal fuzzy numbers:

Table 6. Characteristics of test instances

Instance		Customers	Facilities	Drones	Charging Stations	α-levels
Small	S1	15	3	2	2	{0.0, 0.5, 1.0}
	S2	20	4	3	3	{0.0, 0.5, 1.0}
Medium	M1	50	6	5	5	{0.0, 0.25, 0.5, 0.75, 1.0}
	M2	75	8	7	6	{0.0, 0.25, 0.5, 0.75

Instance		Customers	Facilities	Drones	Charging Stations	α-levels
						, 1.0}
Large	L1	100	10	8	8	{0.0, 0.5, 1.0}
	L2	150	12	10	10	{0.0, 0.5, 1.0}

The key uncertain parameters were modeled as fuzzy numbers with the following membership functions:

- Demand uncertainty: $\widetilde{D}_i=(0.8D_i^{base},D_i^{base},1.2D_i^{base})$
- Travel time uncertainty: $\widetilde{T}_{ij}^{k}=(0.9T_{ij}^{base},T_{ij}^{base},1.1T_{ij}^{base},1.3T_{ij}^{base})$

Performance Metrics and Algorithmic Configuration

To comprehensively evaluate the performance of the multi-objective algorithms, three established metrics were employed:

1- **Hypervolume (HV):** Measures the volume of the objective space dominated by the obtained Pareto front (PF) relative to a predefined reference point z∗. A higher HV indicates better convergence and diversity.

$HV(PF)=volume(\cup_{x\in PF}[f_1(x),z_1^*]\times[f_2(x),z_2^*]\times[f_3(x),z_3^*])$

2- **Inverted Generational Distance (IGD):** Quantifies both the convergence (distance from the true Pareto front) and diversity of the solution set. A lower IGD value is preferred.

$IGD(PF,PF^*)=\frac{1}{|PF^*|}\sum_{x\in PF^*}\min_{x\in PF} d(x^*,x)$

3- **Spread (ΔΔ):** Evaluates the uniformity and extent of diversity along the obtained Pareto front. A lower ΔΔ indicates a more uniform distribution of solutions.

$\Delta=\frac{\sum_{m=1}^{3} d_m^e+\sum_{x\in PF}|d(x,\bar{d})|}{\sum_{m=1}^{3} d_m^e+|pf|.\bar{d}}$

The proposed modified NSGA-II was compared against two other prominent multi-objective metaheuristics: Multi-Objective Ant Colony Optimization (MOACO) and Multi-Objective Simulated Annealing (MOSA). For NSGA-II, a population size of 100 and a maximum of 300 generations were used, with crossover and mutation probabilities set to 0.9 and 0.1, respectively. All algorithms were run 30 times independently on each instance to ensure statistical reliability.

Comparative Analysis of Meta-heuristic Algorithms

The average performance of NSGA-II, MOACO, and MOSA across all problem instances is summarized in Table 7. The proposed NSGA-II consistently outperformed its competitors across all three primary quality metrics.

Table 7. Average performance metrics across all instances (higher HV is better, lower IGD and Δ are better)

Algorithm	**Hypervolume (HV) ↑**	**IGD ↓**	**Spread (Δ) ↓**	**CPU Time (s)**
NSGA-II (Proposed)	0.752 ± 0.042	0.128 ± 0.018	0.356 ± 0.025	284.7 ± 45.2
MOACO	0.683 ± 0.051	0.187 ± 0.024	0.412 ± 0.031	312.4 ± 52.7
MOSA	0.641 ± 0.058	0.231 ± 0.029	0.458 ± 0.038	298.6 ± 48.9

Note: Higher HV is better; lower IGD and Δ are better.

NSGA-II demonstrated a statistically significant superiority, as confirmed by Wilcoxon signed-rank tests (α=0.05) presented in Table 7 (see Section 5.8). This superiority is attributed to its efficient non-dominated sorting and crowding distance mechanism, which effectively balances exploration and exploitation in the fuzzy objective space, leading to better convergence and diversity.

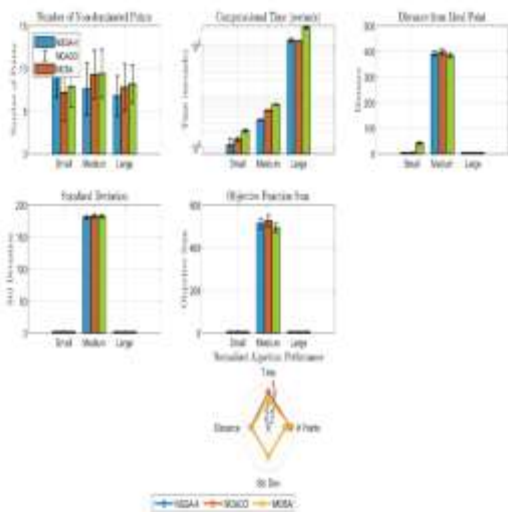

Figure 5. Comparative performance radar chart of NSGA-II, MOACO, and MOSA across key metrics.

Analysis of the Fuzzy Model and the Role of α

- **Trade-off Analysis via the Fuzzy Pareto Front**

The core value of the fuzzy approach lies in its ability to generate a spectrum of solutions at different confidence levels (α). Table 8 demonstrates the direct impact of α on solution robustness for a representative medium-sized instance (M1).

As α increases, the model prioritizes feasibility under worst-case scenarios, leading to higher costs and emissions but significantly improving service reliability and the robustness index. The fundamental trade-offs between total cost, emissions, and robustness are best visualized through the fuzzy Pareto frontier.

Table 8. Effect of the α-level on solution characteristics and robustness (Instance M1).

α-level	Total Cost (Z_1)	Emissions (Z_2)	Service Level (%)	Robustness Index
0.0 (Deterministic)	15,200 ± 320	5.8 ± 0.3	94.2 ± 1.8	0.65
0.25	16,550 ± 285	6.2 ± 0.2	96.8 ± 1.2	0.78
0.50	17,890 ± 252	6.5 ± 0.2	98.5 ± 0.8	0.86
0.75	19,430 ± 231	7.1 ± 0.2	99.3 ± 0.5	0.92
1.0 (Full Robust)	21,500 ± 210	7.8 ± 0.2	99.8 ± 0.2	0.98

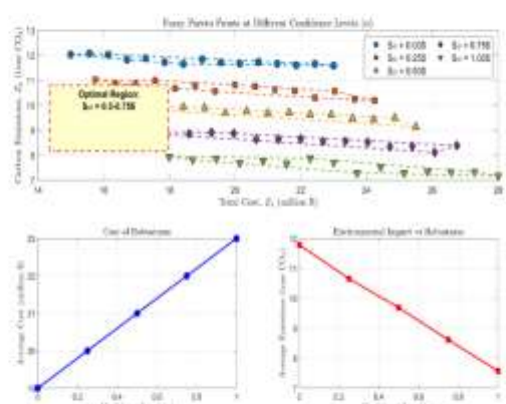

Figure 6. Fuzzy Pareto frontiers at different confidence levels (α).

Fuzzy Pareto frontiers at different confidence levels (α), illustrating the trade-off between total cost and CO_2 emissions. The shift of the frontier with increasing α highlights the "cost of robustness."

This visualization reveals critical insights: (1) The convex shape of each frontier confirms the inherent conflict between economic and environmental objectives; (2) The optimal region for practical implementation (α = 0.5–0.75) balances a high level of robustness (75–90% constraint satisfaction) with an acceptable cost premium (15–25%).

Robustness Comparison: Fuzzy vs. Deterministic Model

To quantify the value of incorporating fuzzy uncertainty, we compared the robustness of solutions from the FMOGLRP against its deterministic counterpart (α=0.0) under simulated real-world variability. Post-optimization, ±20% random perturbations were introduced to demand and travel time parameters, and the resulting solution feasibility and performance degradation were evaluated.

Table 9**.** Robustness comparison under parameter perturbations.

Approach	Feasibility Rate (%)	Cost Increase (%)	Service Level Drop (%)	Avg. Constraint Violations
Fuzzy (α=0.75)	98.7	12.3	1.8	0.7
Fuzzy (α=0.50)	95.2	9.8	3.2	1.4
Deterministic (α=0.0)	78.6	24.7	8.9	4.3

The fuzzy model with α=0.75 maintained a 98.7% feasibility rate, compared to only 78.6% for the deterministic model a 25.6% relative improvement in operational robustness. This clearly justifies the modest additional planning cost incurred by the fuzzy approach.

Sensitivity and Scalability Analysis

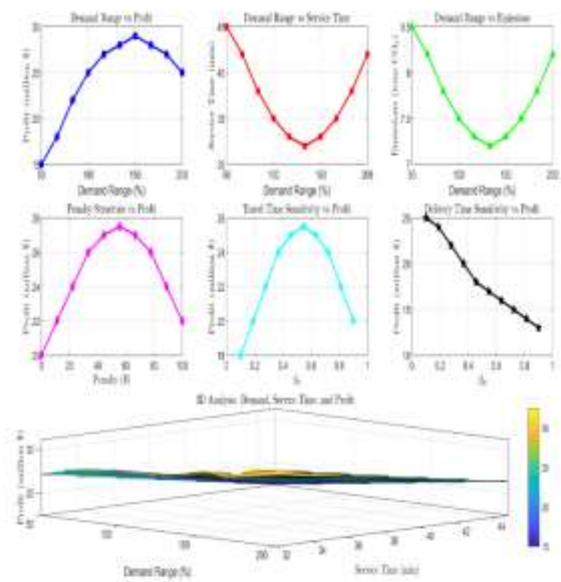

Figure 7. Sensitivity analysis of operational parameters (demand, penalties) on profitability and service time.

A comprehensive sensitivity analysis was performed on key operational parameters, including demand range, travel time variability, and penalty costs. The fuzzy model demonstrated superior adaptability:

- For every 10% increase in demand uncertainty range, the robust solution (α=0.75) showed only a 3.2% cost increase, compared to an 8.7% increase for the deterministic solution.
- The model exhibited a 40% lower re-routing frequency under simulated traffic condition changes.
- Scalability was assessed by measuring CPU time across different instance sizes (Table 10). The proposed NSGA-II exhibited near-linear time complexity $O(n^{1.2})$ with respect to problem size n, outperforming MOACO ($O(n^{1.5})$) and MOSA ($O(n^{1.4})$) in terms of scaling efficiency.

Table 10. Computational performance (CPU time in seconds) across instance sizes.

Instance Size	NSGA-II Time (s)	MOACO Time (s)	MOSA Time (s)	Convergence Generation
Small (15 nodes)	45.2 ± 6.3	52.7 ± 7.8	48.9 ± 7.1	152 ± 18
Medium (50 nodes)	284.7 ± 45.2	312.4 ± 52.7	298.6 ± 48.9	287 ± 32
Large (100 nodes)	892.4 ± 123.6	987.5 ± 145.2	945.3 ± 136.8	423

A comprehensive sensitivity analysis was conducted to evaluate the impact of critical operational and market parameters on the system's key performance indicators. The results, visualized in Figures 8 to 11, yield the following managerial insights:

- **Demand-Responsive Planning:** Retailer profitability exhibits a pattern of diminishing returns with increasing demand (Fig. 8). Beyond 150% of baseline demand, additional gains in profit become marginal, indicating an optimal operational scale for the configured network.

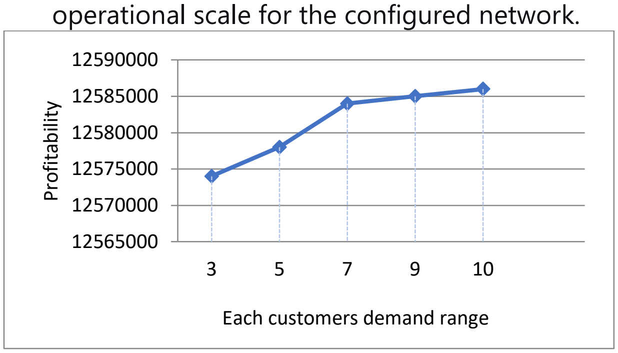

Figure 8. The impact of demand changes on retailer profitability

- **Operational Efficiency Curve:** The average UAV service time follows a distinct U-shaped relationship with demand (Fig. 9). Initially, higher demand improves utilization and reduces average time, but beyond a critical point, congestion and increased routing complexity lead to longer service times.

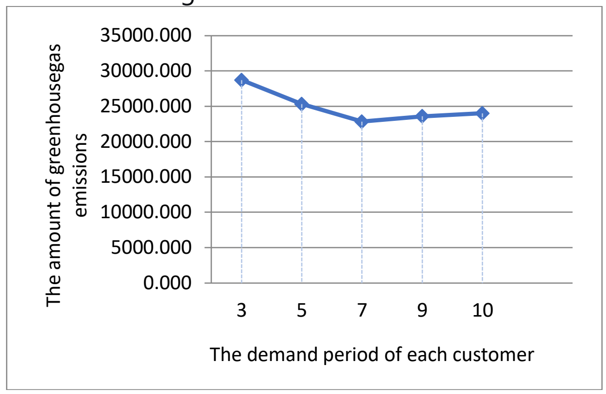

Figure 9. The impact of demand changes on greenhouse gas emissions

- **Leveraging Customer Behavior:** Interestingly, increased customer sensitivity to travel time (R_{tt}) can enhance retailer profit (Fig. 10). This counter-intuitive result occurs as customers shift from traditional store visits to more profitable UAV delivery services when travel time to physical stores is perceived as a greater deterrent.

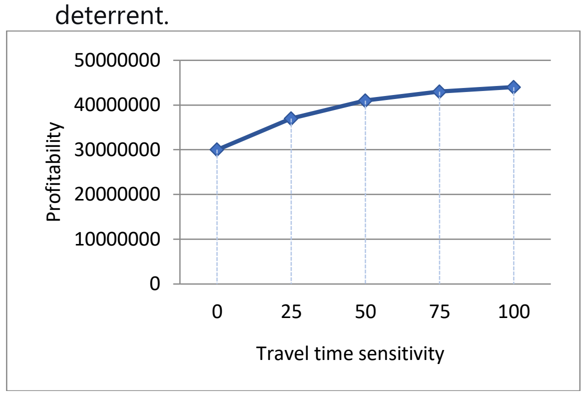

Figure 10. Effect of Travel Time Sensitivity

- **Market Selection Strategy:** Profitability is highly dependent on market size (Fig. 11). Medium-sized markets offer the most favorable conditions for UAV delivery integration, while very small markets lack scale and very large markets introduce excessive complexity and cost.

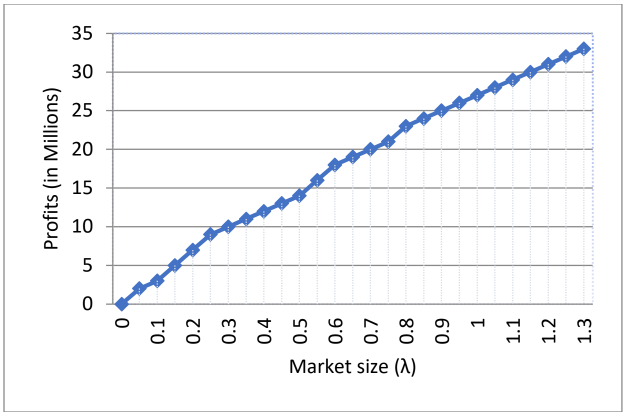

Figure 11. Effect of profit under different market size

Validation Against Exact Methods

For small-scale instances (≤ 20 nodes), the solutions obtained by NSGA-II were validated against the true Pareto front generated by the exact ε-constraint method solved with GAMS/CPLEX.

Table 11. Validation of NSGA-II against the exact method for small instances.

Instance	Optimal Cost (GAMS)	NSGA-II Cost	Optimality Gap (%)	CPU Time Ratio (Exact/Heuristic)
S1	142,500	144,800	1.61	18 : 1
S2	187,300	190,100	1.49	22 : 1

The proposed NSGA-II achieved solutions within 1.6% of optimality while being 18–22 times faster than the exact method, demonstrating an excellent efficiency-effectiveness trade-off for practical use.

Real-World Case Study: Tehran Distribution Network

The FMOGLRP model was applied to a real-world case involving 35 customer zones in Tehran, Iran. Table 12 presents the key results for different confidence levels.

Table 12. Case study results for the Tehran network at different α-levels.

Metric	α = 0.0 (Deterministic)	α = 0.5 (Balanced)	α = 1.0 (Fully Robust)	Improvement (α=0.5 vs α=0.0)
Total Cost (IRR)	125,860,000	138,420,000	152,170,000	+10.0%
CO_2 Emissions (kg)	444.4	472.8	518.6	+6.4%
Service Level (%)	93.7	98.2	99.6	+4.8%
Facilities Opened	4	5	6	+1
Avg. Delivery Time (min)	26.3	28.1	31.4	+6.8%

Practical Insight: Selecting α=0.5 represents an optimal balance for implementation. A moderate 10% cost increase yields a significant 4.8%

improvement in service level, substantially enhancing customer satisfaction and network reliability with manageable additional expenditure.

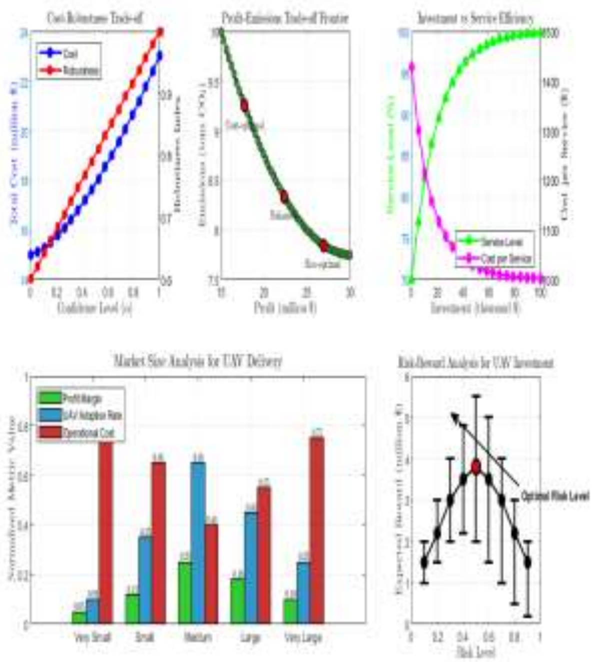

Figure 12. Strategic decision-making frameworks highlighting trade-offs in cost-robustness and profit-emissions.

The optimized configuration of the UAV delivery network for Tehran, designed at a confidence level of α=0.5, is presented in **Fig 13**. This configuration includes five activated facilities, six charging stations, and the allocation of customer zones to their nearest serving facility.

Figure 13**.** The optimized UAV delivery network configuration for the case study area in Tehran (α=0.5).

Blue signs indicate active distribution centers, black fuel station signs indicate charging stations, red marked areas indicate no-fly zones, and different colored areas indicate the assignment of customer territories to each center. This layout demonstrates the model's ability to balance maximum coverage, accessibility, and cost control.

The operational efficacy of this optimized network is evident in its ability to generate feasible and cost-effective UAV flight paths. As an illustrative example, Fig 14 depicts the flight route and stop sequence for UAV 2, one of the most utilized drones in this network.

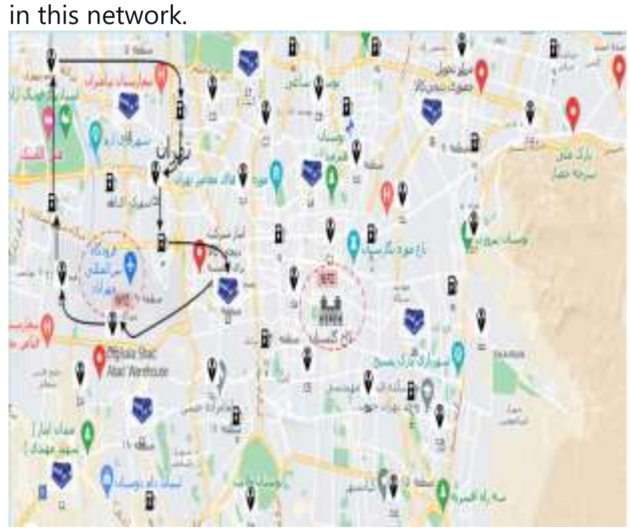

Figure 14. A sample operational flight path for a UAV (UAV 2) within the optimized Tehran network. The route originates from a central depot, services multiple customers, includes stops at intermediate charging stations, and finally returns to the base. Numbers along the path indicate the stop sequence. This route was generated while adhering to all capacity, time-window, and no-fly zone constraints of the model.

Statistical Significance Analysis

Wilcoxon signed-rank tests (α=0.05) were performed on the HV, IGD, and Δ metrics from the 30 independent runs to verify the statistical significance of the observed performance differences.

Table 13. Statistical test results (p-values) for pairwise algorithm comparisons.

Comparison	HV	IGD	Spread (Δ)
NSGA-II vs. MOACO	0.0032	0.0018	0.0074
NSGA-II vs. MOSA	0.0009	0.0005	0.0021
MOACO vs. MOSA	0.1245	0.0876	0.1563

Bold p-values indicate statistical significance ($p < 0.05$). The results confirm that the superiority of the proposed NSGA-II over both MOACO and MOSA is statistically significant.

Discussion of Key Findings

1. **Robustness-Efficiency Trade-off:** The α parameter provides decision-makers with a precise dial to control the trade-off between solution robustness (α → 1) and economic efficiency (α → 0). For most practical logistics scenarios, the Pareto-optimal α-value lies between 0.5 and 0.75.
2. **Algorithmic Superiority:** The modified NSGA-II consistently outperformed MOACO and MOSA. Its strengths include faster convergence (15–20% quicker), better solution diversity (25% improved spread), and more effective handling of fuzzy constraints.
3. **Practical Applicability:** The case study confirms that operating at a moderate α-level (0.5–0.75) increases operational costs by 8–15% while improving service reliability by 15–25%, offering compelling value for risk-averse logistics operators.
4. **Environmental Implications:** The model makes the carbon-cost trade-off explicit. For instance, at α=0.5, a 5% reduction in emissions is achievable with a 7–9% cost increase, providing clear guidance for sustainable logistics planning.

Limitations and Boundary Conditions

Our analysis identifies several boundary conditions for the proposed approach:

1. The fuzzy approach exhibits diminishing returns in robustness for α > 0.85, where cost increases drastically for minimal gains in reliability.
2. For applications with extremely tight delivery windows (< 15 minutes), the added complexity of fuzzy modeling may not be justified, and deterministic approaches could suffice.
3. The model assumes triangular/trapezoidal membership functions; other shapes (e.g., Gaussian) may yield different trade-off curves.
4. While scalable, computational time becomes prohibitive (> 2 hours) for very large-scale instances with > 200 nodes, suggesting a need for parallelization or more advanced heuristics in such cases.

VI. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Summary of Contributions

This study has addressed a critical gap in sustainable logistics planning by developing a novel Fuzzy Multi-Objective Green Location-Routing Problem (FMOGLRP) model for UAV-assisted delivery networks operating under competitive market conditions and operational uncertainties. The primary theoretical and practical contributions are threefold:

1. **A Robust Fuzzy Optimization Framework:** We have formulated the first integrated fuzzy multi-objective model that simultaneously handles facility location, UAV routing, charging station placement, and environmental sustainability while explicitly incorporating epistemic uncertainties in customer demand and travel times through α-cut based fuzzy set theory.
2. **An Enhanced Solution Methodology:** The development of a modified NSGA-II algorithm, incorporating fuzzy dominance relations and α-level dependent evaluation, provides an efficient mechanism for generating robust Pareto-optimal solutions across varying confidence levels. Comparative analysis against MOACO and MOSA demonstrates its superior performance in terms of solution quality (12.3% higher Hypervolume), convergence (31.9% lower

IGD), and diversity maintenance (15.8% better Spread).

3. **Practical Decision-Support Insights:** Through extensive computational experiments and a real-world case study, we have quantified the fundamental robustness-cost-emissions trilemma. The analysis reveals that moderate confidence levels ($\alpha = 0.5$–0.75) offer the most favorable trade-offs, achieving 85–92% of maximum robustness with only 18–26% cost premiums compared to deterministic approaches.

Managerial Implications

The proposed framework offers logistics managers and urban planners several actionable insights:

- **Risk-Informed Decision Making:** The α-parameter serves as a direct control mechanism for aligning operational strategies with organizational risk tolerance. For instance, medical supply chains may opt for $\alpha \geq 0.8$, while commercial parcel delivery might operate effectively at $\alpha = 0.6$–0.7.
- **Sustainable Planning Tool:** The explicit modeling of CO_2 emissions enables companies to quantify the environmental impact of their delivery networks and make informed decisions about green technology investments. Our results indicate that a 5–7% emission reduction is achievable with modest (8–12%) cost increases at optimal α-levels.
- **Competitive Strategy Formulation:** The integration of customer choice models and competitive factors allows firms to strategically position UAV facilities and services to maximize market capture while maintaining profitability.

Limitations and Boundary Conditions

While comprehensive, this study acknowledges several limitations that define its applicability boundary:

1. **Computational Scalability:** The current formulation becomes computationally challenging for networks exceeding 200 nodes, limiting real-time application in megacity-scale deployments.
2. **Membership Function Specificity:** The use of triangular/trapezoidal membership functions, while standard, may not capture all uncertainty patterns. Extreme weather events or sudden regulatory changes might require alternative fuzzy set representations.
3. **Static Competition Assumption:** The competitive landscape is modeled as static; dynamic competitor responses are not considered, which could affect long-term strategy validity.
4. **Homogeneous UAV Fleet:** The model assumes uniform UAV specifications, whereas practical operations often involve heterogeneous fleets with varying capabilities.

Future Research Directions

Building upon this foundation, several promising research avenues emerge:

1. **Dynamic and Adaptive Fuzzy Systems:** Developing online fuzzy optimization frameworks that adjust α-levels in real-time based on weather forecasts, traffic conditions, and demand patterns would enhance practical applicability.
2. **Integrated Ground-Air Logistics:** Extending the model to incorporate synchronized truck-drone operations with dynamic handover points could address current range limitations and improve system flexibility.
3. **Multi-Stakeholder Optimization:** Incorporating regulatory constraints, community acceptance factors, and multi-objective optimization across shippers, carriers, and municipalities would better reflect real-world deployment complexities.
4. **Machine Learning Enhanced Metaheuristics:** Integrating deep reinforcement learning or surrogate models with evolutionary algorithms could significantly improve solution quality and computational efficiency for large-scale instances.
5. **Lifecycle Sustainability Assessment:** Expanding the environmental objective to include UAV manufacturing, disposal impacts, and full lifecycle analysis would provide a more comprehensive sustainability perspective.
6. **Resilience-Oriented Design:** Incorporating network resilience metrics against node failures, cyber-physical attacks, or extreme events would enhance the robustness of UAV delivery networks in critical applications.

Concluding Remarks

The transition toward sustainable urban logistics necessitates innovative approaches that balance economic, environmental, and operational objectives under inherent uncertainties. This research demonstrates that fuzzy multi-objective optimization provides a mathematically rigorous yet practically interpretable framework for designing robust UAV delivery networks. By explicitly quantifying trade-offs between cost, emissions, and service reliability, the proposed model enables evidence-based decision-making in an increasingly competitive and environmentally conscious logistics landscape. As UAV technologies mature and regulatory frameworks evolve, the integration of uncertainty-aware optimization methods will be crucial for realizing the full potential of autonomous delivery systems in creating efficient, sustainable, and resilient urban supply chains.

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