

Facility Location and Routing Optimization for Humanitarian Drone Logistics

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ABSTRACT

Indonesia is vulnerable to natural disasters, which frequently disrupt ground transportation infrastructure and hinder humanitarian aid distribution. In such conditions, drone-based logistics offers a promising alternative for last-mile delivery to affected areas. This study proposes an integrated optimization framework for humanitarian drone logistics that combines a multi-objective Facility Location Problem (FLP) and a Vehicle Routing Problem (VRP). The FLP determines the optimal locations of drone stations to maximize service coverage while minimizing infrastructure and operational costs, and is formulated as a min-max weighted-sum objective with normalized components. The VRP, solved using a Simulated Annealing (SA) algorithm, optimizes pickup-and-delivery routes with multi-trip capability, subject to drone capacity, distance, and operational time constraints. The framework is evaluated using real disaster data from the 2022 Cianjur earthquake in Indonesia. Results show that a small number of strategically located drone stations achieve high service coverage at a reasonable daily cost, with weight coverage approaching completeness. Routing optimization substantially reduces the deployed fleet relative to the FLP upper bound, demonstrating the added value of the VRP stage as a cost-reduction mechanism. The findings demonstrate that integrated strategic and operational optimization significantly enhances the efficiency and feasibility of drone-based humanitarian logistics, and that objective weight tuning can serve as a practical policy lever for balancing coverage, cost, and equity in disaster relief operations.

Keywords: *drone logistics, humanitarian, facility location, vehicle routing*

1. INTRODUCTION

Indonesia is among the countries with a high probability of experiencing natural disasters due to its geographic and geological characteristics. According to data from the National Disaster Management Agency (BNPB, 2025), Indonesia experiences a wide range of disasters, including earthquakes, floods, landslides, volcanic eruptions, extreme weather events, forest and land fires, and coastal abrasion. The impacts of these disasters extend far beyond human casualties, causing severe damage to critical infrastructure, including roads, bridges, public facilities, and transportation networks, thereby significantly hampering ground-based logistics operations.

In 2024, Indonesia recorded a total of 1,918 disaster events (BNPB, 2025), dominated by floods (962 events), extreme weather (410 events), forest and land fires (336 events), landslides (120 events), earthquakes (18 events), coastal abrasion and tidal flooding (13 events), and volcanic eruptions (5 events). These disasters resulted in extensive physical damage, including 9,193 severely damaged houses, 11,169 moderately damaged houses, and 35,858 lightly damaged houses. In addition, numerous educational, healthcare, religious facilities, and bridges were affected. The disasters also led to 462 fatalities and more than 5.5 million displaced people. The spatial distribution of these events spans both mainland and remote island regions, posing substantial challenges for humanitarian logistics, particularly when road and bridge networks are severely damaged or completely inaccessible. Under such conditions, humanitarian logistics must continue to function effectively for timely distribution of essential relief items, such as food, blankets, medicines, and other basic necessities, to affected populations.

Rapid and accurate delivery of relief supplies is critical to reducing human suffering and supporting emergency response efforts (Rabta *et al.*, 2018). However, conventional ground-based transportation often faces severe limitations in post-disaster environments due to infrastructure disruptions, terrain constraints, and limited accessibility. These challenges underscore the urgent need for innovative, resilient humanitarian logistics systems capable of reaching affected areas quickly and efficiently. One promising solution is the use of Unmanned Aerial Vehicles (UAVs), commonly referred to as drones. UAVs offer significant advantages in disaster response contexts, as they can bypass damaged ground infrastructure and access hard-to-reach or isolated areas that are inaccessible to conventional vehicles.

Since 2021, Beehive Drones, a technology startup in Indonesia, has actively developed drone-based logistics systems, including applications in humanitarian and medical supply distribution. One notable initiative involved collaboration with Telkomsel to provide medical logistics delivery during the COVID-19 pandemic, particularly in regions with limited infrastructure. Considering Indonesia's archipelagic geography, Beehive Drones designed a specialized operational system featuring hybrid Vertical Take-Off and Landing (VTOL) drones capable of inter-island flights, dedicated two-way telemetry communication networks for long-distance remote control, and a web-based application for real-time medical supply ordering. The hybrid VTOL configuration enables drones to operate without requiring large take-off and landing areas while maintaining long-range flight capability.

Despite these advancements, multicopter UAVs still face several operational limitations, particularly in terms of payload capacity, battery endurance, and maximum flight range (Dorling *et al.*, 2017; Kuo *et al.*, 2022). These constraints pose significant challenges for large-scale humanitarian logistics operations. Consequently, there is a pressing need to develop optimization algorithms that determine the optimal locations of UAV departure points or drone stations, and efficient delivery routes that account for payload capacity, travel distance, and battery limitations.

This study addresses these challenges by focusing on the joint optimization of drone station locations and UAV routing for humanitarian logistics operations in disaster-affected areas. The proposed approach aims to enhance the efficiency, responsiveness, and reliability of drone-based humanitarian logistics systems, thereby supporting more effective disaster response and relief distribution under severe infrastructure disruption.

Recent studies have extensively explored the application of drones in both commercial and humanitarian logistics, emphasizing their potential to overcome accessibility challenges in disrupted environments. In the logistics domain, research has focused on Vehicle Routing Problems with Drones (VRPD), hybrid truck-drone systems, and energy-aware routing models that account for payload, battery endurance, and synchronization constraints (Dorling *et al.*, 2017; Moshref-Javadi *et al.*, 2021; Murray & Raj, 2020). In humanitarian contexts, drones have been shown to significantly enhance last-mile distribution efficiency in disaster-affected areas (Rabta *et al.*, 2018), and optimization mod-

els have addressed fleet allocation, hub location, and routing decisions (Escribano Macias *et al.*, 2020; Ghelichi *et al.*, 2022). More advanced approaches incorporate uncertainty and robustness in demand and network conditions through stochastic and robust optimization frameworks (Ghelichi *et al.*, 2022; Xin *et al.*, 2025; Zhang *et al.*, 2023). Hybrid truck-drone coordination has also been widely studied to improve response time and accessibility in constrained environments (Xin *et al.*, 2025; Zhang *et al.*, 2021). Despite these significant advances, existing research often treats facility location and routing decisions separately or relies on synthetic datasets, highlighting the need for integrated strategic-operational optimization frameworks validated with real disaster data and realistic UAV constraints. This mirrors a broader pattern in the LRP literature, where many studies treat location and routing sequentially despite evidence that integration yields better solutions (Arevalo-Ascanio *et al.*, 2024). Integrated frameworks have proven valuable elsewhere, Ransikarbum *et al.* (2024) jointly optimized hospital locations and distribution routes via clustering and CVRP, but remain unexplored for UAV-based humanitarian logistics, where flight range and payload constraints add further complexity.

This study contributes to the growing body of literature on drone-based humanitarian logistics by addressing several critical gaps in existing research. First, it explicitly incorporates drone stations as decision variables in humanitarian logistics systems, optimizing their locations based on the spatial distribution of supply and emergency demand points. Second, the study develops a comprehensive UAV-oriented VRP that accounts for key operational constraints specific to drones, including payload capacity, battery consumption, maximum flight range, and feasibility of multi-stop delivery. Third, unlike many prior studies that rely solely on synthetic or simulated data, this research validates the proposed model using a real humanitarian case study from BNPB and operational drone specifications provided by Beehive Drones. By integrating realistic operational data with advanced optimization modeling, this research offers both methodological contributions and practical insights to support more efficient, responsive, and deployable drone-based humanitarian logistics systems in disaster-prone regions.

2. LITERATURE REVIEW

2.1. Drones in Logistics

The use of UAVs, commonly known as drones, in the logistics sector has become a growing area of research interest. Drones offer significant advantages over conventional transportation modes, particularly for short-distance or last-mile delivery. Their ability to bypass road obstacles, such as traffic congestion, makes drones an efficient option for reducing delivery time and operational costs. In addition, drones can reach remote areas and difficult-to-access locations, providing substantial benefits for logistics distribution in regions with limited infrastructure. However, drones also face several operational limitations, including limited payload capacity, restricted battery endurance, and short flight range, which constrain their large-scale application (Dorling *et al.*, 2017; Kuo *et al.*, 2022).

To address these limitations, hybrid approaches that inte-

grate drones with trucks have been widely developed. This model, known as the truck–drone hybrid delivery system, uses trucks as mobile hubs that deploy and retrieve drones at strategic locations along delivery routes. Studies indicate that this approach not only improves delivery time efficiency but also significantly reduces truck travel distance. In some cases, drone launch locations are not restricted to customer locations but also include flexible locations specifically designed to enhance drone utilization. For example, research by Murray and Raj (2020) demonstrates that the use of multiple drones within a single fleet can substantially reduce delivery time (Kitjacharoenchai & Lee, 2019; Murray & Raj, 2020). Furthermore, Wang *et al.* (2022) investigated the truck–drone hybrid routing problem with time-dependent road travel times in the context of urban logistics.

Beyond time efficiency, synchronization between trucks and drones is a critical aspect of hybrid delivery systems. Models such as the Synchronized Truck-and-Drone Routing Problem explore how trucks and drones can operate concurrently to serve customers in the most efficient manner. Effective synchronization ensures that drones can be launched and retrieved by trucks at the appropriate times and locations, thereby optimizing resource utilization. Moshref-Javadi *et al.* (2021) showed that improved synchronization can reduce customer waiting times by up to 60% compared to truck-only delivery systems.

Determining optimal routes for trucks and drones has become a central focus of related research. The VRP with Drones (VRPD) is one of the most widely used models for integrating truck and drone routing decisions. This model incorporates various operational constraints, such as payload capacity, battery endurance, and service time windows, to ensure efficient logistics distribution. Research also indicates that heuristic algorithms, such as ant colony optimization (ACO) and variable neighborhood search (VNS), are highly effective in solving these complex routing problems, particularly at large scales (Huang *et al.*, 2022; Kundu *et al.*, 2022).

The application of drones is not limited to commercial logistics but is also highly relevant in humanitarian logistics, especially in emergency situations such as natural disasters. Drones have significant potential to deliver essential supplies, such as food and medicines, to areas difficult to access due to infrastructure damage. Models such as the Pickup-to-Delivery Drone Routing Problem (PDDRP) have been specifically designed to address these logistical needs. Research by Gómez-Lagos *et al.* (2022) demonstrates that drones can accelerate logistics distribution in emergency situations, particularly in regions where road access is disrupted.

Another major challenge in drone logistics implementation is optimizing energy use and cost efficiency. Dorling *et al.* (2017) developed a model that accounts for energy consumption as a function of payload weight and drone battery capacity. Their findings indicate that energy optimization can significantly reduce operational costs and extend drone flight range, thereby improving the effectiveness of drone-based logistics systems. In addition, several studies have explored multitrip routing models, in which drones perform multiple round trips between depots and customers

to enhance fleet utilization efficiency (Dorling *et al.*, 2017; Moshref-Javadi *et al.*, 2021).

2.2. Drones in Humanitarian Logistics

Natural disasters are unpredictable events that can cause extensive damage and have severe impacts on communities and the environment. In post-disaster situations, logistics plays a crucial role in saving lives and delivering aid to affected populations. However, humanitarian logistics operations often face significant challenges, such as limited transportation access, workforce constraints, and severe time pressure.

One major obstacle in disaster response is limited access to affected areas. In such situations, transportation becomes a critical factor in delivering humanitarian aid. A study by Setiabudi and Wydiadana (2019) shows that the success of logistics aid delivery to disaster-affected areas depends heavily on the selection of appropriate transportation modes and effective coordination between humanitarian organizations and local governments.

In addition to transportation, technology plays an important role in disaster response. Research by Kundu *et al.* (2022) indicates that information and communication technologies can enhance the efficiency of disaster management. Technologies such as geographic information systems (GIS), drones, and sensor networks can support damage assessment, area surveillance, and faster logistics distribution.

In the context of humanitarian assistance, the use of drones, or UAVs, has emerged as a promising solution to logistical challenges in disaster-affected areas. Drones can reach locations inaccessible due to damaged or impassable infrastructure, enabling rapid and efficient delivery of humanitarian aid (Rabta *et al.*, 2018). In addition to delivery tasks, drones can be used for disaster-area mapping, infrastructure damage assessment, and distribution of essential supplies such as food, water, and medical equipment. For example, Zhang *et al.* (2021) demonstrated that drones can be used to survey transportation networks after disasters, helping to identify optimal routes for logistics distribution.

Recent studies also highlight that logistical and healthcare access challenges in Indonesia are not limited to disaster events but are deeply rooted in the country's archipelagic geography. Mangoma and Sulistiadi (2024) highlight critical healthcare gaps in Indonesia's island communities, including limited infrastructure, workforce shortages, and geographical isolation, which severely restrict timely access to essential health services during emergencies. These findings underscore the need for innovative, flexible logistics solutions to support the rapid distribution of medical supplies to underserved regions.

Despite the significant potential of drones in humanitarian logistics, several technical challenges remain, including limited battery endurance, adverse weather conditions, and the need for charging infrastructure. Edwards *et al.* (2024) and Rejeb *et al.* (2021) identified these as among the most persistent barriers to large-scale drone deployment in humanitarian settings, with battery life and adverse weather conditions being particularly critical. Escribano Macias *et al.* (2020) explicitly modeled battery consumption, charging time, and hub infrastructure as core operational constraints in their UAV logistics framework. Ghelichi *et al.* (2022) further acknowledged weather sensitivity and drone failure as

practical implementation challenges that remain to be addressed in future research.

In recent years, many studies have applied optimization models to improve drone use in humanitarian logistics. One of the earliest contributions is Rabta *et al.* (2018), who propose a drone fleet optimization model for last-mile distribution in disaster relief operations. Their work demonstrates how UAVs can be systematically allocated to serve demand points under capacity and range constraints, highlighting the potential of optimization models to improve response time in emergency logistics.

Facility location problems (FLP) have also received considerable attention in the literature. Escribano Macias *et al.* (2020) developed an optimization model to determine optimal UAV hub locations for rapid medical deliveries, showing that strategic placement of drone hubs significantly enhances service coverage and delivery speed in emergency healthcare contexts. Ghelichi *et al.* (2022) also studied drone location and scheduling problems in humanitarian logistics. The study formulates mathematical optimization models that jointly consider drone base locations and operational schedules. The facility location component of the proposed framework is related to the Maximal Covering Location Problem (MCLP), first introduced by Church and Velle (1974), which seeks to locate a fixed number of facilities to maximize the total demand covered within a given service distance. The MCLP has since been extended in numerous directions, including humanitarian logistics applications. Li *et al.* (2018) proposed cooperative maximal covering models for humanitarian relief chain management, demonstrating the applicability of the MCLP framework to disaster response contexts. For drone-specific applications, Chauhan *et al.* (2019) formulated a Maximum Coverage Capacitated Facility Location Problem with range-constrained drones, which shares structural similarities with the FLP proposed in this study in terms of jointly determining facility locations and drone assignments subject to coverage and range constraints. More recently, Vural (2026) applied a maximum coverage model directly to drone-based humanitarian logistics in a post-disaster earthquake scenario, incorporating drone operational constraints including battery capacity and payload limits. The FLP proposed in this study builds upon and extends these foundations in three key ways. First, it adopts a multi-objective formulation that simultaneously maximizes coverage and minimizes station installation and drone operational costs, whereas the classical MCLP and most of its variants treat coverage as the sole objective. Second, it introduces drone fleet sizing constraints based on payload capacity, trip frequency, and flight range, which are not present in the standard MCLP. Third, it incorporates supply point assignment constraints that reflect the real infrastructure requirements of humanitarian drone operations, ensuring that each opened station is served by at least one supply point with existing logistical infrastructure. Together, these extensions are necessary to capture the operational realities of drone-based disaster relief that the classical MCLP does not address.

On the routing side, several studies focus on solving complex VRP involving drones. Sacramento *et al.* (2019) propose an adaptive large neighborhood search (ALNS) meta-

heuristic for the VRP with Drones (VRPD) and demonstrate its effectiveness on large-scale instances. Shadlou *et al.* (2023) further advance the state of the art by applying a logic-based Benders decomposition approach to a combined repair crew routing and drone scheduling problem after natural disasters, illustrating how decomposition techniques can tackle highly complex, integrated humanitarian logistics problems.

To improve operational efficiency, hybrid truck–drone systems are frequently proposed in humanitarian logistics. In this approach, trucks serve as mobile hubs that deploy drones to hard-to-reach locations. Hybrid truck–drone systems have also been widely studied using optimization models. Zhang *et al.* (2021) formulate an optimization model for humanitarian relief network assessment using a collaborative truck-and-drone system, while Zhang *et al.* (2023) introduce a robust optimization framework for drone routing in humanitarian transportation networks to enhance system resilience under uncertainty. More recently, Xin *et al.* (2025) proposed a two-stage distributionally robust optimization model for truck–drone-supported humanitarian relief networks corresponding to pre-disaster and post-disaster decision-making. Khameneh *et al.* (2026) further introduced a bi-objective model coordinating trucks and drones for last-mile humanitarian aid delivery under disrupted conditions, addressing infrastructure damage and accessibility constraints.

Uncertainty is another critical feature of humanitarian operations that has been addressed through advanced optimization approaches. Ghelichi *et al.* (2022) incorporate uncertain demand from disaster-impacted populations into drone logistics models, proposing optimization frameworks that improve robustness against demand variability. More recently, Ghelichi *et al.* (2024) introduce a simulation-based performance evaluation model to support decision-making in drone location and delivery scheduling.

Overall, these studies demonstrate that optimization models ranging from deterministic and stochastic programming to robust optimization, decomposition techniques, and metaheuristics play a central role in enabling effective drone-based humanitarian logistics. However, despite these advances, challenges remain in jointly optimizing drone station locations and routing decisions using real operational data and realistic UAV constraints, indicating opportunities for further research in this area.

3. PROBLEM DESCRIPTION

To address the drone-based humanitarian logistics problem, this study adopts a two-phase optimization approach consisting of a FLP and a VRP. In the first phase, the FLP is formulated to determine the optimal locations of drone stations, assign demand and supply points to each station, and estimate the required number of drones while balancing coverage maximization and cost minimization. The results of the FLP inform strategic-level decisions that define the system's operational scope. In the second phase, a VRP is developed to optimize daily drone operations by determining efficient pickup-and-delivery routes with multitrip capability, ensuring that each drone departs from and returns to its assigned drone station. This two-phase structure allows strategic location and operational routing decisions to be addressed in

an integrated yet computationally tractable manner.

3.1. Drone-FLP

The drone FLP mathematical model adopts a multi-objective formulation, with objectives to maximize drone station coverage and minimize costs associated with drone station construction and operations. The drone count is used to estimate the maximum number of drones, which will later serve as an upper bound in the VRP. This facility location model is used to determine the optimal locations of drone stations, assign customers (demand points) to them, estimate the number of drones required at each station, and allocate supply points to them.

The model considers a set I of demand points, each associated with a demand w_i , a set J of candidate locations for drone stations, and a set S of supply points. Each demand point is assigned to a drone station, with the maximum number of drone stations limited to P . The distances between demand points and supply points and their assigned drone stations are constrained by a maximum distance D , where D is set to 50% of the maximum drone flying range. This constraint ensures that drones can complete round-trip flights without exceeding their maximum flight range. In addition, each opened drone station must be associated with at least one supply point for collecting relief packages. The number of drones is estimated using a rough approximation based on half the maximum flying range, which influences the decision to open drone stations. Equations (1) to (14) present the complete mathematical formulation of the FLP model.

Sets:

- I : set of demand points (shelter posts)
- J : set of candidate locations for drone stations
- S : set of supply points

Parameters:

- d_{ij} : distance between demand point $i \in I$ and drone station $j \in J$
- k_{sj} : distance between supply point $s \in S$ and drone station $j \in J$
- θ : maximum flying range of a drone
- W : maximum payload capacity of a drone per trip (kg)
- K : maximum number of trips a drone can perform per day
- W_{eff} : effective payload capacity per drone per day (kg), where $W_{\text{eff}} = W \times K$
- c : fixed installation cost per drone station per day (constant for all $j \in J$)
- o : drone operational cost per day (drone rental cost + operating cost) per drone (constant for all $j \in J$)
- P_{max} : maximum number of drone stations that can be opened
- w_i : demand weight at shelter post $i \in I$ (kg)
- B : maximum fleet sizes of drone
- M : sufficiently large constant (big- M)
- α, β, γ : non-negative objective weights, $\alpha + \beta + \gamma = 1$
- $W^{\min}, W^{\max}$: minimum and maximum possible coverage, where $W^{\min} = 0$ and $W^{\max} = |I|$
- $C^{\min}, C^{\max}$: minimum and maximum possible installation cost, where $C^{\min} = 0$ and $C^{\max} = c \cdot |J|$

- $O^{\min}, O^{\max}$: minimum and maximum possible operational cost, where $O^{\min} = 0$ and $O^{\max} = o \cdot B$

Decision Variables:

- $y_j = \begin{cases} 1, & \text{if a drone station is opened at location } j \\ 0, & \text{otherwise} \end{cases}$
- $x_{ij} = \begin{cases} 1, & \text{if demand point } i \text{ is served by station } j \\ 0, & \text{otherwise} \end{cases}$
- $a_{sj} = \begin{cases} 1, & \text{if supply point } s \text{ is assigned to station } j \\ 0, & \text{otherwise} \end{cases}$
- z_j : estimated number of drones assigned to drone station j

Objective Function:

Maximize coverage and minimize facility and operational costs:

$$\begin{aligned} \text{maximize } F = & \alpha \cdot \frac{\sum_{i \in I} \sum_{j \in J} w_i x_{ij} - W^{\min}}{W^{\max} - W^{\min}} \\ & - \beta \cdot \frac{\sum_{j \in J} c y_j - C^{\min}}{C^{\max} - C^{\min}} - \gamma \cdot \frac{\sum_{j \in J} o z_j - O^{\min}}{O^{\max} - O^{\min}} \end{aligned} \quad (1)$$

Constraints:

$$\sum_{j \in J} x_{ij} \leq 1, \quad \forall i \in I \quad (2)$$

$$x_{ij} \leq y_j, \quad \forall i \in I, j \in J \quad (3)$$

$$d_{ij} \cdot x_{ij} \leq \theta, \quad \forall i \in I, j \in J \quad (4)$$

$$\sum_{j \in J} y_j \leq P_{\text{max}} \quad (5)$$

$$z_j \cdot W_{\text{eff}} \geq \sum_{i \in I} w_i x_{ij}, \quad \forall j \in J \quad (6)$$

$$z_j \cdot K \geq \sum_{i \in I} x_{ij}, \quad \forall j \in J \quad (7)$$

$$z_j \geq \frac{1}{D} \sum_{i \in I} d_{ij} x_{ij}, \quad \forall j \in J \quad (8)$$

$$z_j \leq M y_j, \quad \forall j \in J \quad (9)$$

$$k_{sj} \cdot a_{sj} \leq \theta, \quad \forall s \in S, j \in J \quad (10)$$

$$a_{sj} \leq y_j, \quad \forall s \in S, j \in J \quad (11)$$

$$\sum_{s \in S} a_{sj} \geq y_j, \quad \forall j \in J \quad (12)$$

$$x_{ij}, y_j, a_{sj} \in \{0, 1\}, \quad \forall i \in I, j \in J, s \in S \quad (13)$$

$$z_j \in \mathbb{Z}_{\geq 0}, \quad \forall j \in J \quad (14)$$

Equation (1) defines the objective function of the FLP, which aims to simultaneously maximize demand coverage, minimize drone station installation costs, and minimize drone operational costs. To ensure commensurability across objectives with different units and scales, a scaling approach is applied to each component. The installation cost term is normalized by $C^{\max} = c \cdot |J|$, representing the maximum possible installation cost if all candidate stations were opened. The operational cost term is normalized by $O^{\max} = o \cdot B$, representing the worst-case operational cost assuming a maximum fleet size of B drones deployed across the network. For the coverage component, the numerator $\sum_{i \in I} \sum_{j \in J} w_i x_{ij}$ represents the total demand weight

served, while $W^{\max} = |I|$ is used as a scaling proxy that effectively balances the relative contribution of each objective and ensures that meaningful trade-offs are produced across all three components. Since the minimum value of each component is zero, i.e., $W^{\min} = C^{\min} = O^{\min} = 0$, the formulation simplifies to dividing each term by its respective scaling bound. The three objectives are then combined using a weighted-sum approach, where the non-negative weights α , β , and γ reflect the relative importance of each objective, subject to $\alpha + \beta + \gamma = 1$.

Constraint (2) ensures that each demand point can be served by at most one drone station, allowing for the possibility that some demand points remain unserved. Constraint (3) guarantees that demand points can only be assigned to drone stations that are opened. Constraint (4) ensures that the distance between each demand point and its assigned drone station does not exceed the maximum flying range D . Constraint (5) limits the total number of drone stations that can be established to at most P . Constraints (6), (7), and (8) jointly determine the minimum number of drones required at each station j . Constraint (6) ensures that the total payload capacity of drones at station j is sufficient to deliver all assigned demand, where W_{eff} denotes the effective payload capacity per drone per day, accounting for multi-trip operations. Constraint (7) ensures that the number of drones is sufficient to serve all assigned shelter posts, given that each drone can perform at most K trips per day. Constraint (8) ensures that the total flight distance can be covered by the available drones, where the minimum number of drones is proportional to the cumulative distance to all assigned demand points relative to the maximum service range D . Constraint (9) enforces that drones can only be allocated to drone stations that are opened by applying a big-M constraint. Constraint (10) restricts the distance between supply points and drone stations to remain within the drone's maximum flying range, while constraint (11) ensures that supply points can only be allocated to opened drone stations. Constraint (12) requires that each opened drone station is supported by at least one supply point. Finally, constraints (13) and (14) define the domains of the decision variables, where x_{ij} , y_j , and a_{sj} are binary variables, and z_j is a non-negative integer representing the estimated number of drones at each station.

The drone fleet estimation produced by the FLP serves two distinct roles in the integrated framework. First, the drone count z_j at each opened station j is passed to the VRP as the upper bound Z , ensuring that the routing stage always has sufficient drone capacity to serve the assigned demand points. The VRP then determines the actual deployed fleet through explicit route optimization, which in this study could reduce the fleet from FLP estimate to VRP deployment, reflecting the efficiency gained from detailed routing that the aggregate FLP cannot capture. Second, incorporating drone operational cost in the FLP objective function ensures that station location decisions are made with awareness of fleet implications. Without this term, the FLP could select station locations that appear cost-efficient in terms of installation cost and coverage but inadvertently require a disproportionately large drone fleet. By including drone cost in the objective, the FLP steers the location solution toward configurations that are jointly efficient across coverage, installa-

tion cost, and expected fleet size. The FLP drone estimation simultaneously constrains the VRP and guides the strategic location decision toward operationally sound configurations.

3.2. Drone-VRP

The mathematical model for the Drone-VRP is designed to accommodate pickup-and-delivery operations and drones' multi-trip capability. The objective of this VRP is to minimize the total daily operational cost of delivering humanitarian aid using drones. Each drone route originates at a drone station, where the drone travels to a supply point to collect relief packages destined for demand points. Only after completing the pickup operation is the drone allowed to proceed to the assigned demand points. Once all designated demand points have been served, the drone returns to its originating drone station. Consequently, each drone route always starts and ends at the same drone station. Since the number of drones is predetermined at each station, they must return to their respective stations after completing each route. Each drone is subject to a maximum payload capacity Q and a maximum flying range constraint. In addition, there is a daily operational time limit, T_{max} , that restricts the total number of trips a drone can perform in a single day. Equations (15) to (32) present the complete mathematical formulation of the drone-based VRP.

Sets:

- D : set of drones
- S : set of supply points
- C : set of demand points
- P : set of opened drone stations
- N : set of all nodes
- T : set of all trips

Parameters:

- d_{ij} : distance between node i and node j
- w_c : demand of customer c
- Q : maximum payload capacity of a drone
- n : total number of nodes
- ϕ_1 : regression intercept for drone range constraint
- ϕ_2 : regression slope for drone range constraint
- s : service time per node (minutes)
- T_{max} : maximum operational time per day (minutes)
- e : penalty cost for unserved demand points (Rp)
- c_{ij} : travel cost from node i to node j , defined as $c_{ij} = \delta \cdot d_{ij}$, where δ is the cost per unit distance (Rp/km)
- f : fixed operational cost per drone per day (Rp)
- v : drone flight velocity (km/min)
- Z : maximum number of drones available at the station, determined by the FLP solution
- p : index of the drone station serving as the depot for the current VRP instance, where $p \in P$
- τ : drone charging time between consecutive trips (minutes)

Decision Variables:

- $x_{ijdt} = \begin{cases} 1, & \text{if drone } d \text{ on trip } t \text{ travels from node } i \text{ to node } j \\ 0, & \text{otherwise} \end{cases}$
- u_{idt} : position (sequence order) of drone d at node i on trip t
- $k_d = \begin{cases} 1, & \text{if drone } d \text{ is used} \\ 0, & \text{otherwise} \end{cases}$

- $z_{dt} = \begin{cases} 1, & \text{if drone } d \text{ is assigned to trip } t \\ 0, & \text{otherwise} \end{cases}$
- $a_c = \begin{cases} 1, & \text{if customer } c \text{ is not served} \\ 0, & \text{otherwise} \end{cases}$

3.2.1. Objective Function

$$\min(\sum_{i \in N} \sum_{j \in N} \sum_{d \in D} \sum_{t \in T} c_{ij} x_{ijdt} + \sum_{d \in D} f k_d + \sum_{c \in C} e a_c) \quad (15)$$

3.2.2. Constraints

$$\sum_{i \in N \setminus \{c\}} \sum_{d \in D} \sum_{t \in T} x_{icdt} + a_c = 1, \quad \forall c \in C \quad (16)$$

$$\sum_{i \in N \setminus \{j\}} x_{ijdt} = \sum_{k \in N \setminus \{j\}} x_{jkdt}, \quad \forall j \in N, d \in D, t \in T \quad (17)$$

$$u_{idt} - u_{jdt} + n x_{ijdt} \leq n - 1, \quad \forall i, j \in N \setminus \{p\}, i \neq j, d \in D, t \in T \quad (18)$$

$$u_{pdt} = 0, \quad \forall d \in D, t \in T \quad (19)$$

$$u_{sdt} \geq 1 - n \left(1 - \sum_{i \in N \setminus \{s\}} x_{isdt} \right), \quad \forall s \in S, d \in D, t \in T \quad (20)$$

$$u_{sdt} \leq u_{cdt} + n \left(2 - \sum_{i \in N \setminus \{s\}} x_{isdt} - \sum_{i \in N \setminus \{c\}} x_{icdt} \right), \quad \forall s \in S, c \in C, d \in D, t \in T \quad (21)$$

$$\sum_{s \in S} \sum_{i \in N \setminus \{s\}} x_{isdt} \geq \frac{1}{|C|} \sum_{c \in C} \sum_{i \in N \setminus \{c\}} x_{icdt}, \quad \forall d \in D, t \in T \quad (22)$$

$$\sum_{c \in C} \sum_{i \in N \setminus \{c\}} x_{icdt} \geq \sum_{s \in S} \sum_{i \in N \setminus \{s\}} x_{isdt}, \quad \forall d \in D, t \in T \quad (23)$$

$$\sum_{s \in S} \sum_{i \in N \setminus \{s\}} x_{isdt} \leq 1, \quad \forall d \in D, t \in T \quad (24)$$

$$\sum_{c \in C} \sum_{i \in N \setminus \{c\}} w_c x_{icdt} \leq Q, \quad \forall d \in D, t \in T \quad (25)$$

$$x_{iidt} = 0, \quad \forall i \in N, d \in D, t \in T \quad (26)$$

$$\sum_{i \in N} \sum_{j \in N \setminus \{i\}} d_{ij} x_{ijdt} \leq \phi_1 + \phi_2 \left(\sum_{c \in C} \sum_{i \in N \setminus \{c\}} w_c x_{icdt} \right), \quad \forall d \in D, t \in T \quad (27)$$

$$z_{dt} = \sum_{j \in N \setminus \{p\}} x_{pjdt}, \quad \forall d \in D, t \in T \quad (28)$$

$$k_d \geq z_{dt}, \quad \forall d \in D, t \in T \quad (29)$$

$$\sum_{d \in D} k_d \leq Z \quad (30)$$

$$\sum_{j \in N \setminus \{p\}} x_{pj,d,t+1} \leq \sum_{j \in N \setminus \{p\}} x_{pjdt}, \quad \forall d \in D, t \in T : t < |T| \quad (31)$$

$$\sum_{i \in N} \sum_{j \in N \setminus \{i\}} \sum_{t \in T} \frac{d_{ij}}{v} x_{ijdt} + \sum_{i \in N} \sum_{j \in N \setminus \{i\}} \sum_{t \in T} s x_{ijdt} + \left(\sum_{t \in T} z_{dt} - 1 \right) \tau \leq T_{\max}, \quad \forall d \in D \quad (32)$$

Equation (15) defines the objective function, which aims to minimize the total operational cost of the drone logistics system. This cost consists of three main components: drone travel costs between nodes, fixed costs associated with

drone utilization, and penalty costs incurred for unserved demand points. Through this formulation, the objective function seeks to balance cost efficiency with the level of service provided. Constraint (16) ensures that each demand point can be served at most once; if a demand point is not served, the corresponding penalty variable is activated, causing the unmet demand to contribute to the penalty cost. Constraint (17) represents the flow balance condition, guaranteeing that whenever a drone enters a node, it must also leave that node. Constraint (18) is a subtour elimination constraint that prevents the formation of closed cycles that are not connected to a drone station. Constraint (19) specifies that the visit order index of the drone station is always initialized to zero. Constraint (20) enforces that if a supply point is visited, its visit order must be at least one, since the zero position is exclusively assigned to the drone station. Constraint (21) regulates the visit sequence by ensuring that supply points are visited before demand points, thereby guaranteeing a logical pickup-and-delivery order within each trip. Furthermore, constraint (22) ensures that every served customer is associated with at least one visited supply point, while constraint (23) guarantees that each visit to a supply point is followed by at least one delivery to a customer. Constraint (24) limits each trip to visiting at most one supply point. Constraint (25) ensures that the total payload carried in a single trip does not exceed the maximum drone capacity Q . In addition, constraint (26) prevents drones from traveling from a node back to the same node (self-loops). Constraint (27) imposes a maximum flight distance based on a linear regression relationship between travel distance and total payload, which serves as an approximation of the drone's battery limitation. The coefficients $\phi_1 = 15.23$ km and $\phi_2 = -0.09577$ km/kg were obtained from regression on manufacturer flight-test data, with $\phi_2 < 0$ reflecting the expected reduction in achievable range as payload increases. To regulate drone availability and usage, constraint (28) defines the variable z_{dt} as an indicator of whether drone d is active in trip t , while constraint (29) enforces that the drone usage variable k_d is set to one if the drone is used in any trip. Constraint (30) limits the total number of drones that can be operated to Z . Constraint (31) ensures the continuity of trips by preventing a drone from executing trip $t + 1$ unless trip t has already been performed. Finally, constraint (32) imposes a maximum daily operational time $T_{\max}$ for each drone, accounting for travel time, service time, and charging time between trips, except that no charging time is required after the final trip.

4. SOLUTION METHOD

This study adopts a two-stage optimization framework to solve the drone-based humanitarian logistics problem, consisting of a strategic planning stage and an operational routing stage. In the first stage, the Drone-FLP is solved using an exact optimization approach. The FLP is formulated as a mathematical optimization model and implemented in Python using the Cplex Solver. An exact method is used to ensure the model produces optimal solutions that fully satisfy all predefined constraints. This approach enables rigorous verification and validation of the proposed FLP model before its use in subsequent analyses. The core components

of the model: sets, parameters, decision variables, objective function, and constraints are explicitly translated into the programming environment. The solution process for the FLP is implemented in Python using the CPLEX solver.

In the second stage, the results from the FLP, including the selected drone station locations and the estimated number of drones at each station, are used as input parameters for the VRP. Preliminary computational experiments indicate that solving the VRP using exact methods requires excessive computation time, making it impractical for disaster response scenarios that demand rapid decision-making. Consequently, an alternative solution approach based on metaheuristic optimization is adopted to generate near-optimal solutions in a significantly shorter time. This approach is considered more suitable for emergency situations where timely and efficient logistics decisions are critical. In this study, the Simulated Annealing (SA) algorithm is employed as the metaheuristic solution method for the VRP.

The metaheuristic algorithm employed in this study is SA, inspired by the physical annealing process in metallurgy, in which controlled cooling allows a material to reach a stable state with minimum energy. This concept is adapted to optimization problems to balance exploration and exploitation of the solution space. The pseudocode of SA is shown in Algorithm 1.

In this study, the classical SA algorithm is modified using a customized acceptance criterion that prioritizes solutions that require fewer drones, thereby promoting operational efficiency. The core mechanism of SA allows the algorithm to accept inferior solutions in a controlled manner based on an acceptance probability that depends on the current temperature: at higher temperatures, worse solutions are more likely to be accepted, while at lower temperatures acceptance becomes increasingly selective. This mechanism enables the algorithm to escape local optima and search for better global solutions.

The parameters used in the SA algorithm include the initial temperature, cooling rate, final temperature, number of iterations per temperature level, and the maximum number of non-improving iterations. The stopping criteria are satisfied when the temperature reaches the predefined final value or when no improvement in the solution is observed for a specified number of iterations.

The algorithm's overall workflow begins with generating an initial solution. If the initial solution is infeasible (e.g., contains unserved demand points), the generation process is repeated up to a predefined number of attempts to ensure a valid starting point. The search process is organized as a nested loop: the outer loop controls the gradual temperature reduction, while the inner loop explores neighboring solutions at each temperature level.

Algorithm 1 SA for Drone-VRP

```

1: Input:  $T_{init}, T_{final}, \alpha, N_{iter}, N_{nonImp}$ 
2: Generate initial solution  $S$ 
3: attempts  $\leftarrow 0$ 
4: while  $S$  is infeasible and attempts  $< 10$  do
5:   Regenerate initial solution  $S$ 
6:   attempts  $\leftarrow$  attempts + 1
7: end while
8:  $S_{curr} \leftarrow S, S_{best} \leftarrow S$ 
9:  $T \leftarrow T_{init}$ 
10: while  $T > T_{final}$  do
11:    $noImp \leftarrow 0, iter \leftarrow 0$ 
12:   while  $iter < N_{iter}$  and  $noImp < N_{nonImp}$  do
13:     Generate neighbor solution  $S'$ 
14:     if  $S'$  is feasible then
15:       Compute cost difference  $\Delta = f(S') - f(S_{curr})$ 
16:       Evaluate number of drones and unserved demand points
17:       if  $S'$  uses fewer drones or fewer unserved demand points then
18:         Accept  $S'$ 
19:       else if  $S'$  uses more drones then
20:         Apply penalty to  $\Delta$ 
21:         Accept  $S'$  with probability  $e^{-\Delta/T}$ 
22:       else if  $\Delta \leq 0$  then
23:         Accept  $S'$ 
24:       else
25:         Accept  $S'$  with probability  $e^{-\Delta/T}$ 
26:       end if
27:       if  $S'$  is accepted then
28:          $S_{curr} \leftarrow S'$ 
29:         if  $S_{curr}$  is better than  $S_{best}$  then
30:            $S_{best} \leftarrow S_{curr}$ 
31:            $noImp \leftarrow 0$ 
32:         else
33:            $noImp \leftarrow noImp + 1$ 
34:         end if
35:       else
36:          $noImp \leftarrow noImp + 1$ 
37:       end if
38:       end if
39:        $iter \leftarrow iter + 1$ 
40:     end while
41:      $T \leftarrow \alpha \cdot T$ 
42:   end while
43: Return  $S_{best}$ 

```

At each iteration, a candidate solution is generated using one of several neighborhood move operators. The SA implementation employs seven neighborhood move operators, each applied with equal probability through a random shuffle mechanism. All operators are subject to feasibility checks covering payload capacity, maximum flight distance, and total drone operation time constraints. The operators are:

- a) **Move Between Trips (Relocate):** a randomly selected customer is removed from its current trip and inserted at a random feasible position in a different trip. This operator explores inter-trip customer reallocation.
- b) **Swap Between Trips:** one customer from each of two

randomly selected trips is exchanged. This operator improves load balancing across trips without changing the number of demand points per trip.

- c) **Swap Within Trip:** two demand points within the same trip are selected at random and their positions are exchanged. This operator improves the visiting sequence within a single trip.
- d) **Reverse Segment (2-opt):** a contiguous segment of demand points within a randomly selected trip is reversed. This operator is equivalent to a 2-opt move and is effective at eliminating route crossings.
- e) **Supply Point Swap:** the supply point of a randomly selected trip is replaced with a different supply point. This operator is specific to this problem structure, where each trip must begin at a supply point before visiting demand points.
- f) **Insert Unserved:** an unserved customer is inserted at the best feasible position in a randomly selected existing trip. This operator reduces the number of unserved demand points.
- g) **Minimize Drones:** all trips are repacked across drones by sorting trips in descending order of weight and greedily assigning them to the minimum number of drones. This operator is accepted only if it reduces the total number of drones used.

The acceptance criterion is redesigned as follows: a new solution is immediately accepted if it reduces the number of drones used or increases the number of served demand points. If the new solution requires more drones, a large penalty is added to its cost before applying the Metropolis acceptance rule, making acceptance highly unlikely except at high temperatures. If the number of drones remains unchanged, the standard Metropolis criterion is applied. This strategy enables broader exploration during early iterations and gradual intensification as the temperature decreases.

The algorithm employs two types of stopping criteria. The global stopping criterion terminates the algorithm once the final temperature is reached. A local stopping criterion, the maximum number of non-improving iterations, limits exploration at each temperature level to improve computational efficiency. When no improvement is observed for a specified number of iterations, the algorithm proceeds to the next temperature level. The non-improvement counter is reset whenever a better solution is found, or the temperature is updated, ensuring a balanced trade-off between solution quality and computational time.

5. RESULTS AND DISCUSSION

5.1. Case Study and Data Description

The case study used to evaluate the proposed models and algorithms is the 2022 Cianjur Earthquake. The disaster caused extensive damage, displacing approximately 114,683 people to emergency shelters across the affected areas. The large number of displaced individuals posed significant challenges for humanitarian aid distribution, particularly due to widespread damage to road infrastructure caused by the earthquake. Many roads were severely damaged or completely cut off, substantially hindering ground-based logistics operations and delaying the delivery of relief supplies to affected communities. Consequently, drone-based logis-

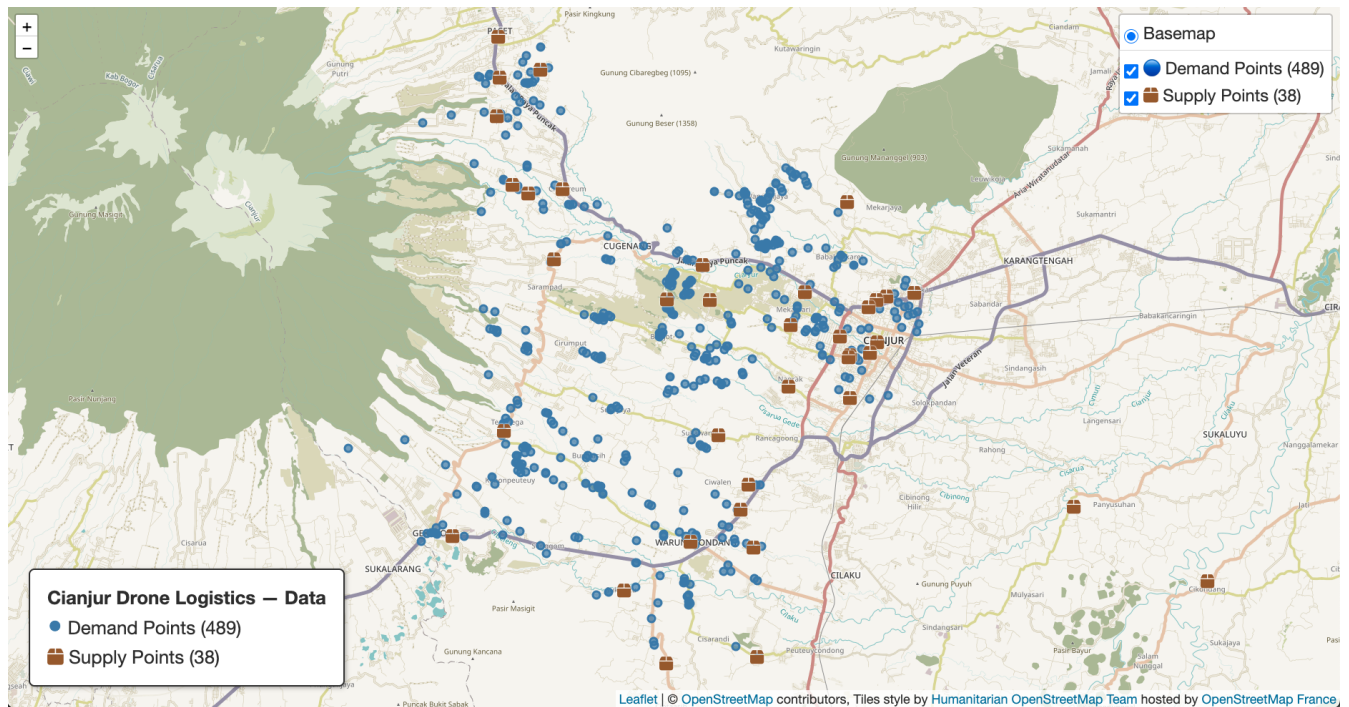
tics was explored as an alternative to support more effective, timely humanitarian aid delivery.

The data used in this study were collected during the post-disaster response period following the 2022 Cianjur Earthquake, covering humanitarian aid distribution from November 2022 to March 2023, or approximately five months. Data collection involved identifying the geographic coordinates of emergency shelters, healthcare facilities, and logistics warehouses that were operational during the emergency response phase. In this study, emergency shelters are defined as demand points, while healthcare facilities and logistics warehouses are treated as supply points. In addition, all supply points are also considered as candidate locations for establishing drone stations. All data were obtained from the official website of the National Disaster Management Agency of Indonesia (BNPB, 2025). The processed datasets and model implementation files generated during the study are available at <https://osf.io/wkbm5>.

Each demand point was assigned a unique identifier. In total, 489 demand points and 38 supply points were identified, as shown in Figure 1. Demand points are represented by blue circular markers, while supply points are indicated by brown box icons. The spatial distribution of demand points indicates that many shelters are relatively close to one another, with important implications for route planning and drone utilization. The dataset also includes information on supply points, which simultaneously serve as candidate drone station locations. The majority of supply points consist of healthcare facilities, supplemented by several logistics warehouses operated by the Regional Disaster Management Agency (BPBD). The supply points, which simultaneously serve as candidate drone station locations, are relatively well dispersed across the area, providing potential coverage to most demand clusters. Accordingly, the maximum number of drone stations P is set to 38, equal to the total number of supply point locations. This choice is motivated by the assumption that drone station construction is feasible at all supply point locations, as these sites already possess the necessary supporting infrastructure, including electricity access, road accessibility, and maintenance facilities that are prerequisites for drone station operation.

Demand weights were calibrated using the SPHERE Humanitarian Standards (Sphere Association, 2018), which provide internationally recognized minimum standards for humanitarian response. The four technical chapters include Minimum Standards in key response sectors: Water Supply, Sanitation and Hygiene Promotion (WASH); Food Security and Nutrition; Shelter and Settlement; and Health. Water Supply, Sanitation and Hygiene Promotion (WASH) is assigned 2.0 kg per person, comprising 1.5 kg for water supply and 0.5 kg for sanitation and hygiene. Food Security and Nutrition is assigned 2.8 kg per person, comprising 2.0 kg for food and 0.8 kg for infant and young child nutrition. Shelter and Settlement is assigned 2.2 kg per person, comprising 1.0 kg for shelter materials, 1.0 kg for clothing, and 0.2 kg for education supplies. Health is assigned 0.5 kg per person.

Given the time-critical nature of food and medical supplies in disaster response, the drone is assigned to deliver exclusively for the Food Security & Nutrition and Health categories. This prioritization reflects the operational role of

**Figure 1** Demand and Supply Locations.

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drones as emergency couriers rather than primary logistics vehicles. Accordingly, the drone demand per shelter post is computed as 10% of the estimated total Food Security & Nutrition and Health relief requirement, capped at the drone payload limit of 30 kg. For shelter posts where needs were recorded as fully met or where need categories were not documented, a minimum demand of 10% of a randomly drawn baseline between 1 and 10 kg is assigned to reflect residual or latent need, ensuring all shelter posts are considered in the optimization.

Table 1 Multicopter Drone Specifications

Specification	Value
Type	Multicopter
Flight Range	Up to 15 km
Flying Height	Up to 120 m
Payload Weight	Up to 30 kg
Maximum Speed	Up to 12 m/s
Battery Capacity	400 Wh
Diameter	2 m
Charging time	90 minutes
Service time	15 minutes
Materials	Carbon Composite

The drone used for humanitarian logistics operations in this study is a multicopter-type drone. The drone specification data are primarily sourced from Beehive Drones. Table 1 presents the technical specifications of the multicopter drone adopted in this study, while Table 2 summarizes the corresponding cost components incorporated into the optimization model.

Table 2 Drone Cost Parameters

Cost Type	Fixed Cost	Daily Cost
Drone Station Construction (c)	Rp 9,750,000 per station (5 months)	Rp 65,000 per station
Drone Rental	Rp 1,713,157 per drone per month	Rp 57,105 per drone
Drone Operational	Rp 131,000 per drone per day	Rp 131,000 per drone
Electricity Cost	Rp 38.53 per km	—

For the baseline scenario, equal weights are assigned to all three objectives, with $\alpha = \beta = \gamma = 1/3$, reflecting a neutral trade-off assumption in the absence of explicit stakeholder preference data. This equal-weight configuration treats coverage maximization, station installation cost minimization, and drone operational cost minimization as equally important, and serves as the reference point for the sensitivity analysis presented in Section 5.3

5.2. Computational Results

Based on the computational results of the Drone-FLP, the obtained objective value is 5.238. The solver achieved an optimal solution within 30.44 seconds using CPLEX 22.1.1. The objective function value can be decomposed into three components: coverage of 16.742 ($\alpha = 0.333$), normalized station installation cost of 0.211 ($\beta = 0.333$), and normalized drone operational cost of 0.820 ($\gamma = 0.333$), yielding a combined objective value of $5.581 - 0.070 - 0.273 = 5.238$. When the original parameter values are used without normalization, the maximized coverage corresponds to 405 shelter posts served across 8 opened drone stations with a total fleet of 82 drones, resulting in a total daily cost of Rp 15,944,610. Table 3 summarizes the results of the FLP.

Table 3 Summary of Multi-Objective FLP Results

Station	Number of Demand Points	Total Demand (kg)	Number of Drones	Number of Supply Points
Station A	50	818.31	10	29
Station E	65	1,048.97	13	30
Station F	75	1,397.23	15	24
Station K	50	1,248.11	11	22
Station M	50	1,156.42	10	11
Station AB	25	474.23	5	5
Station AI	60	1,259.87	12	15
Station AJ	30	783.70	6	23
Total	405	8,186.84	82	–

Based on Table 3, a total of 8 drone stations are opened. These stations serve 405 out of 489 demand points (shelter posts), resulting in a coverage level of 82.8%. The weight coverage reaches 99.5%, with a total of 8,186.84 kg served out of the total estimated demand of 8,230.48 kg across all 489 shelter posts, indicating that although 84 shelter posts remain unserved, they account for only 0.5% of the total estimated demand weight. The estimated total number of drones required is 82. The number of drones at each opened station will subsequently serve as the upper bound on the number of drones available per station in the VRP. Each drone station is also assigned more than one supply point, in accordance with the predefined constraints.

Figure 2 illustrates the spatial distribution of the FLP optimization results across the Cianjur disaster area. Each color in the figure represents a different drone station and its corresponding assigned demand points (shelter posts). The eight opened drone stations, Station A, E, F, K, M, AB, AI, and AJ, are marked with location pin icons, while the demand points assigned to each station are represented by circular markers in the corresponding color. Gray circular markers indicate the 84 unserved shelter posts, and brown square markers represent the supply points. The connecting lines between each station and its assigned demand points illustrate the service coverage area of each station. As can be observed from the figure, the opened stations are distributed across the study area to cover spatially distinct clusters of demand points, reflecting the model's ability to balance coverage across geographically dispersed shelter posts. Station F serves the largest cluster (75 shelter posts) in the northeastern part of the area, while Station AB covers the smallest cluster (25 shelter posts) in the southwestern region. The unserved demand points are scattered across the map, predominantly in areas with lower demand. The FLP results are subsequently used as input to the VRP model to determine the optimal delivery routes for each station.

The SA algorithm employed in this research involves five key parameters: initial temperature, cooling rate, final temperature, iterations per temperature, and maximum number of non-improving iterations. Based on the results of a preliminary evaluation, the best-performing parameter configuration was identified as follows: an initial temperature of 100°C, a cooling rate of 0.99, a final temperature of 0.1, 1,000 iterations per temperature level, and 150 maximum

non-improving iterations. This parameter setting was subsequently adopted for all computational experiments in the case study to balance solution quality and computational efficiency.

The SA algorithm was applied to the main case study, incorporating data from each drone station to identify the optimal routing solution for each location. To ensure the reliability and robustness of the results, five independent replications were performed at each station, given the stochastic nature of metaheuristic algorithms, which may yield different solutions across runs. Among the five outcomes, the minimum objective function value was selected as the best solution for the corresponding station.

Table 4 presents the VRP results for each of the eight opened drone stations, including the best and average costs across replications. The standard deviation of the objective function values across replications is consistently small, ranging from 0.0 (Stations AB and AJ, where identical solutions were obtained in all five runs) to 45.6 (Station E), indicating that the SA algorithm produces stable and reproducible solutions. The remaining analysis is therefore based on the best cost obtained across the five replications.

To assess the solution quality of the SA algorithm, a benchmark comparison was conducted on Station AB, the smallest VRP instance with 25 customers, using CPLEX 22.1.1 as the exact solver. CPLEX was allowed a maximum computation time of one hour, after which it terminated with an MIP gap of 0.10% and a total cost of Rp 754,942.04 with 4 drones deployed. The SA algorithm converged on the same instance in 34.99 seconds, producing a total cost of Rp 754,957.20 with 4 drones, a deviation of only 0.002% from the CPLEX solution. This result demonstrates that the SA algorithm delivers near-optimal solutions at a fraction of the computational time required by an exact solver. For larger instances such as Station F with 75 customers, exact solving is expected to be considerably more time-consuming, further justifying the use of SA as the solution method for this study. The metaheuristic approach is particularly well-suited to humanitarian disaster response contexts, where computational speed is a critical operational requirement.

Across all stations, a total of 67 drones are deployed to serve 405 shelter posts, with a total best daily routing cost of Rp 12,638,547.71. This routing cost covers distance-based

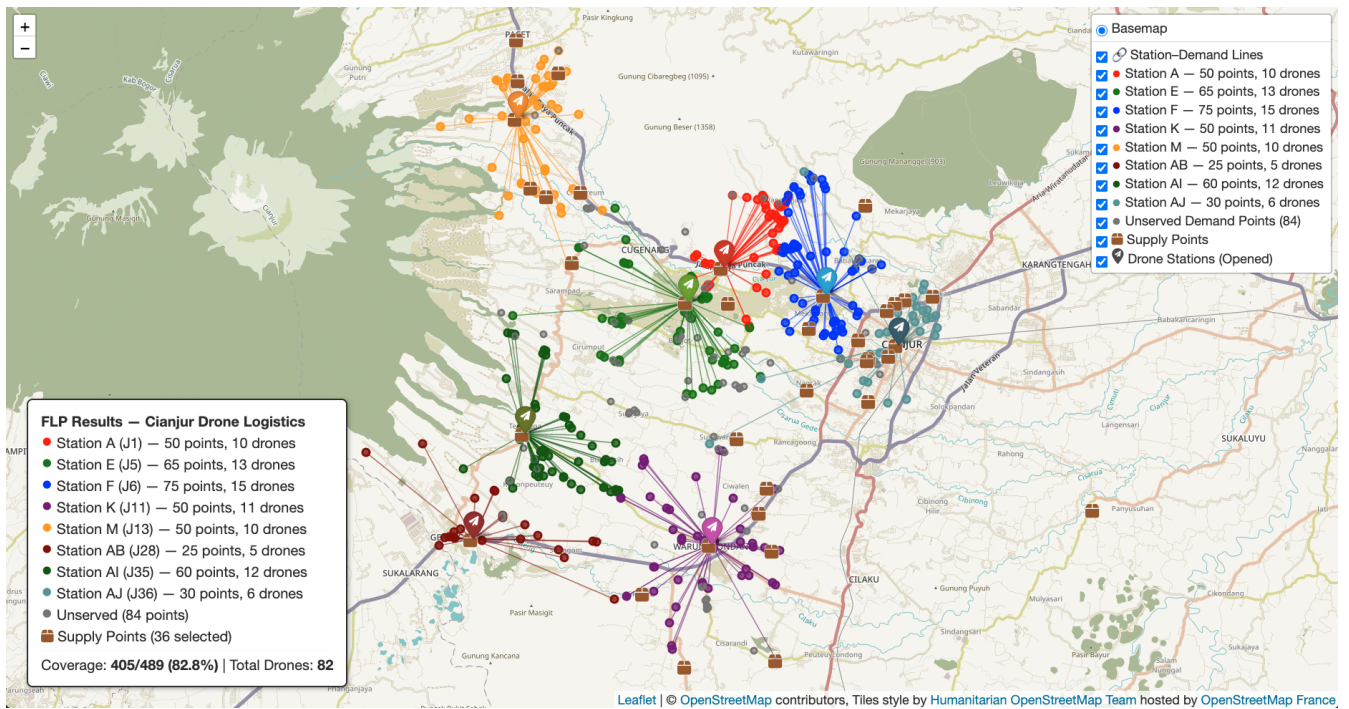


Figure 2 FLP results

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travel costs and drone operational costs incurred during delivery routes, and is separate from the station installation cost reported in the FLP results. Notably, the number of drones actually used in the VRP is consistently lower than or equal to the upper bound established by the FLP across all stations, ranging from 60% utilization at Station A (6 out of 10 drones) to 100% utilization at Station AJ (6 out of 6 drones). In total, 67 out of the 82 drones allocated by the FLP are utilized, corresponding to an overall fleet utilization rate of 81.7%. This indicates that the FLP upper bounds are conservative but effective, providing sufficient capacity while leaving room for operational flexibility.

Station F records the highest routing cost (Rp 2,262,324.00) and the largest fleet size (12 drones), consistent with its role as the station serving the most shelter posts (75 demand points). Conversely, Station AB incurs the lowest routing cost (Rp 754,957.20) with only 4 drones serving 25 shelter posts. The maximum drone operation time across all stations ranges from 626.5 to 688.6 minutes, all within the 720-minute daily operational limit, confirming that all routes are feasible with respect to the time constraint.

Based on Table 4, the total best daily routing cost across all eight drone stations is Rp 12,638,594.71, with a total of 67 drones deployed to serve 405 demand points. This represents the aggregate routing cost required in a single day to deliver relief supplies to all served shelter posts. Operational costs are strongly influenced by the number of drones deployed and the total flight distance, as drone operational expenses and distance-based travel costs are the two main cost components.

It is important to note that the FLP total daily cost of Rp 15,944,610 and the VRP routing cost of Rp 12,638,594.71 measure different things. The FLP cost comprises station installation cost and the drone operational cost based on

the upper-bound fleet of 82 drones estimated at the strategic planning level, and is used to guide station location decisions. The VRP routing cost, comprises distance-based travel cost and drone operational cost for the 67 drones actually deployed through route optimization, and does not include station installation cost. The separately reported saving of approximately Rp 2,821,575 reflects the reduction in drone operational cost achieved by deploying 67 rather than 82 drones (15 drones $\times$ Rp 188,105 per drone per day), and specifically quantifies the efficiency gain of the VRP routing stage in reducing the required fleet size.

Figure 3 illustrates the routing structure obtained from the optimization using the SA algorithm. Each color in the figure corresponds to a different drone, as indicated in the legend. The visualization shows the flight trips, each beginning at a drone station, proceeding to a supply point, then to customer locations, and finally returning to the originating drone station, thereby forming a complete routing cycle. This visualization demonstrates that the proposed model and algorithm operate as intended: each route satisfies the drone distance and capacity constraints and reflects a realistic operational structure suitable for field implementation.

5.3. Sensitivity Analysis

To examine the effect of each weight on the solution, three groups of scenarios were constructed by varying one weight at a time from 0.1 to 0.9 in increments of 0.2, while the remaining two weights were kept equal and adjusted proportionally. Specifically, Group A varies the coverage weight α with $\beta = \gamma = (1 - \alpha)/2$, Group B varies the installation cost weight β with $\alpha = \gamma = (1 - \beta)/2$, and Group C varies the drone operational cost weight γ with $\alpha = \beta = (1 - \gamma)/2$. The detailed results are presented in Table 5, and the corresponding trends are illustrated in Figure 4.

The results reveal clear and interpretable trends across all

Table 4 VRP Results per Drone Station (5 Replications)

Station	# Drones (VRP/FLP)	# Demand Points	Max Drone Time (min)	Best Cost (Rp)	Avg Cost (Rp)	Stddev
Station A	6/10	50	681.8	1,132,005.23	1,132,013.40	14.5
Station E	10/13	65	637.6	1,886,417.61	1,886,455.30	45.6
Station F	12/15	75	661.8	2,262,335.94	2,262,369.39	40.3
Station K	10/11	50	643.5	1,886,738.95	1,886,745.27	12.9
Station M	9/10	50	655.0	1,697,950.05	1,697,956.60	13.4
Station AB	4/5	25	625.1	754,957.20	754,957.20	0.0
Station AI	10/12	60	611.1	1,886,398.73	1,886,417.92	17.3
Station AJ	6/6	30	628.8	1,131,791.00	1,131,791.00	0.0
Total	67/82	405	–	12,638,594.71	12,638,706.08	–

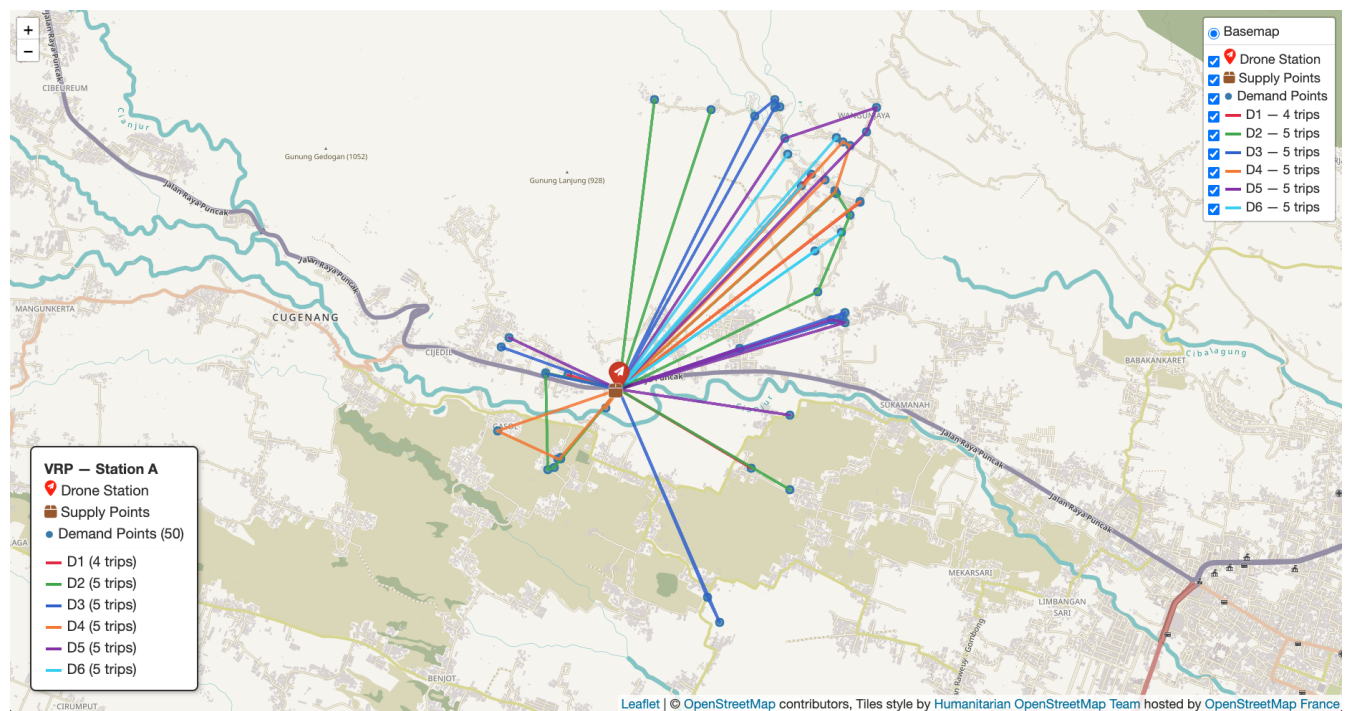


Figure 3 VRP Results: Route Visualization for Drone Station A

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three groups. In Group A, increasing α consistently raises coverage from 69.9% to 99.6% and fleet size from 70 to 100 drones, at the expense of a higher daily cost (from Rp 13.6 million to Rp 19.4 million), confirming that coverage maximization comes with a cost trade-off. In Group B, increasing β reduces the number of opened stations from 9 to 3, while coverage remains relatively stable between 79.6% and 83.0%, except at the extreme value of $\beta = 0.9$, where the solver consolidates demand into very few stations, paradoxically increasing drone count to 137 and daily cost to Rp 25.9 million. In Group C, increasing γ successfully reduces the drone fleet from 112 to 49, but at the cost of significantly reduced coverage, from 97.5% to 50.1%, as the solver trades service breadth for operational efficiency.

A maximum computation time of 3,600 seconds was imposed for each scenario. Within this time limit, 3 out of 15 scenarios had not yet reached a proven optimal solution. However, the MIP gaps for those three cases are very small,

with a maximum of 0.21%, indicating that the solutions are near-optimal and well within the acceptable threshold commonly adopted in the operations research literature. Scenarios C3, C4, and C5 terminated with MIP gaps of 0.06%, 0.13%, and 0.21%, respectively. The increasing computational difficulty in Group C suggests that extreme drone operational cost prioritization leads to a more complex search space, likely due to the solver exploring a larger number of station configurations with minimal drone fleets.

The sensitivity analysis trends are further illustrated in Figure 4. Figure 4a shows that the number of opened stations varies most dramatically when the installation cost weight β increases, declining from 9 to 3 stations, while varying the coverage weight α keeps the number of stations relatively stable at 7–9, and varying the Operational Cost weight γ shows a non-monotonic pattern, peaking at 10 stations before declining. Figure 4b highlights the anomalous behavior when $\beta = 0.9$, where the drone count spikes to 137, the

Table 5 Sensitivity Analysis: Multi-Objective Weight Scenarios (Groups A, B, C)

Scenario	α	β	γ	# Stations	Coverage (%)	Weight Cov. (%)	Daily Cost (Rp)	# Drones
<i>Group A — Varying α (Coverage Weight), $\beta = \gamma = (1 - \alpha)/2$</i>								
A1	0.1	0.45	0.45	7	69.9	96.9	13,622,350	70
A2	0.3	0.35	0.35	8	82.8	99.5	15,944,610	82
A3	0.5	0.25	0.25	8	91.0	99.8	17,449,450	90
A4	0.7	0.15	0.15	8	98.2	100.0	19,142,395	99
A5	0.9	0.05	0.05	9	99.6	100.0	19,395,500	100
<i>Group B — Varying β (Installation Cost Weight), $\alpha = \gamma = (1 - \beta)/2$</i>								
B1	0.45	0.10	0.45	9	81.8	99.5	15,633,400	80
B2	0.35	0.30	0.35	8	82.8	99.5	15,944,610	82
B3	0.25	0.50	0.25	5	83.0	99.5	18,006,870	94
B4	0.15	0.70	0.15	5	83.0	99.5	18,006,870	94
B5	0.05	0.90	0.05	3	79.6	98.9	25,965,385	137
<i>Group C — Varying γ (Operational Cost Weight), $\alpha = \beta = (1 - \gamma)/2$</i>								
C1	0.45	0.45	0.10	5	97.5	100.0	21,392,760	112
C2	0.35	0.35	0.30	7	84.3	99.5	16,632,030	86
C3	0.25	0.25	0.50	9	78.7	99.2	15,069,085	77
C4	0.15	0.15	0.70	10	71.6	97.9	13,817,350	70
C5	0.05	0.05	0.90	8	50.1	85.2	9,737,145	49

highest across all scenarios, despite having only 3 opened stations, reflecting the high operational burden placed on a minimal station network. Figure 4c confirms the diverging behavior: increasing the coverage weight α produces a clear upward trend in coverage from 69.9% to 99.6%, while increasing the operational cost weight γ leads to a sharp decline from 97.5% to 50.1%, and increasing the installation cost weight β results in relatively stable coverage throughout. Figure 4d reveals that weight coverage is considerably less sensitive to objective weight changes than count coverage, remaining above 96% when varying α and β , and only dropping below 90% at the extreme value of $\gamma = 0.9$. This confirms that unserved shelter posts are predominantly those with minimal residual demand, as discussed in the previous section. Finally, Figure 4e shows that increasing the operational cost weight γ consistently produces the lowest total daily cost across all weight levels, while increasing the installation cost weight β produces the highest cost at extreme values, driven by the anomalous spike at $\beta = 0.9$. These visualizations collectively confirm that the three objective weights govern fundamentally different aspects of the logistics system, and that the baseline equal-weight configuration ($\alpha = \beta = \gamma = 1/3$) represents a well-balanced operating point among the scenarios tested.

5.4. Discussion

The results of this study provide important strategic and operational insights into the design and implementation of drone-based humanitarian logistics systems in disaster-affected regions. By integrating a multi-objective FLP with a VRP and solving both using a modified SA algorithm, the proposed framework demonstrates that coordinated optimization across planning levels can substantially improve both service coverage and resource efficiency.

The proposed integrated FLP-VRP framework offers sev-

eral advantages that warrant comparison with related studies in the literature. Escribano Macias *et al.* (2020) developed a bi-stage operational planning approach for UAV-based humanitarian logistics, in which hub selection and vehicle routing are solved as two separate sequential stages. While their framework achieves meaningful coverage within a 24-hour operational window, the separation between the hub location and routing stages introduces a risk of suboptimal solutions, as the hub selection stage cannot anticipate the routing implications of its decisions. In contrast, the integrated FLP-VRP approach proposed in this study allows the location and routing decisions to inform one another, resulting in a station configuration that is inherently compatible with the subsequent delivery routes. This is evidenced by the fleet utilization rate of 81.7% achieved in the VRP stage, where 67 out of 82 FLP-allocated drones were effectively deployed, indicating that the FLP upper bounds are both realistic and operationally feasible rather than overly conservative.

Ghelichi *et al.* (2022) addressed drone logistics under demand location uncertainty using a stochastic Chance Constrained Programming formulation, which is methodologically more sophisticated in handling uncertain demand scenarios. However, their model treats demand as a single payload per drone per trip and does not consider multi-trip operations within a daily operational window, nor does it incorporate supply point constraints that reflect real infrastructure conditions. The present study addresses both of these aspects: drones perform multiple trips per day subject to charging time and operational time constraints, and each station must be served by at least one supply point with an established logistical infrastructure. Furthermore, while Ghelichi *et al.* (2022) focus on minimizing total delivery disutility under probabilistic demand, this study employs a multi-objective formulation that simultaneously bal-

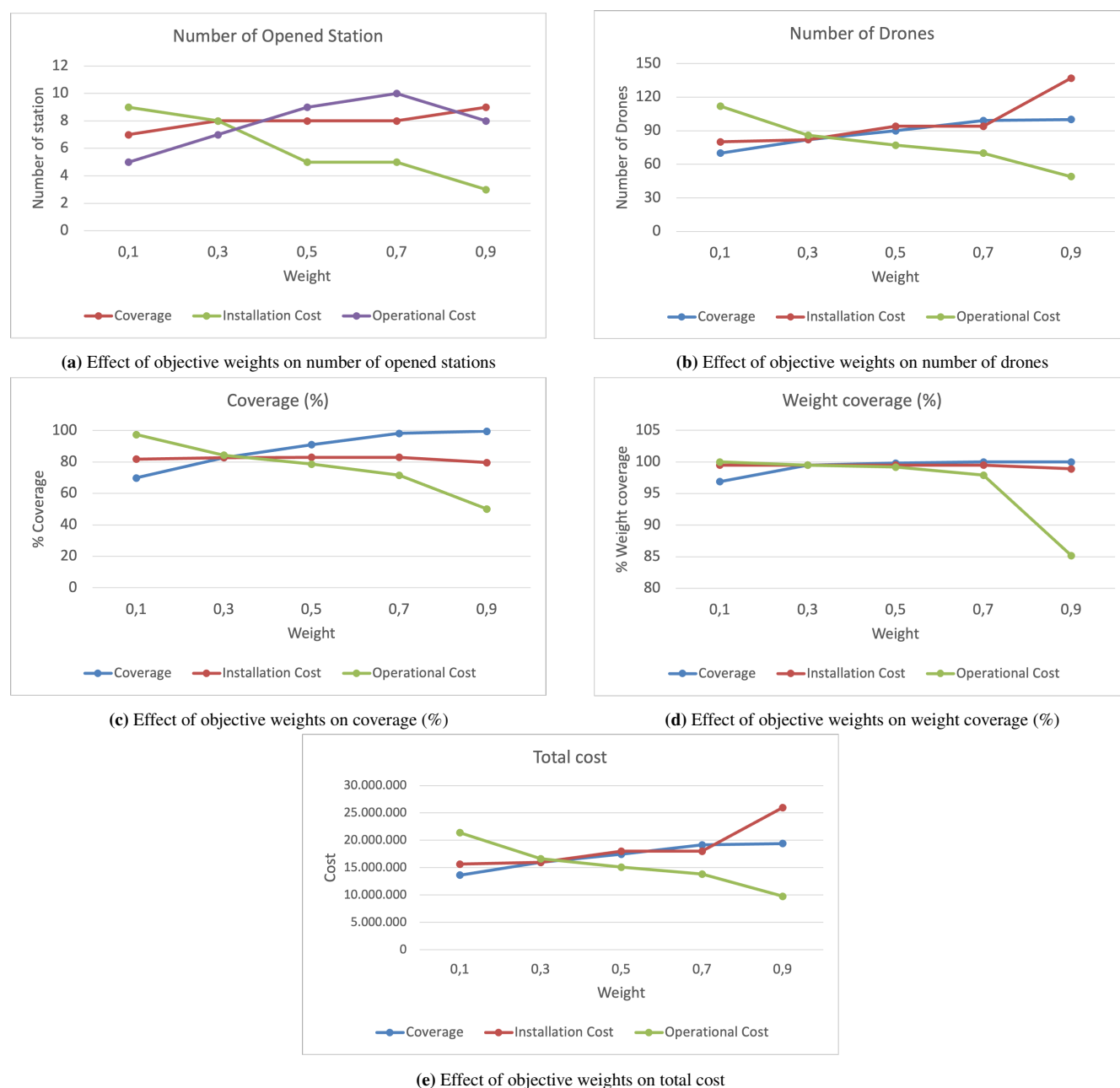


Figure 4 Sensitivity Analysis Trends: Effect of Varying Objective Weights

ances coverage, station installation cost, and drone operational cost, making the trade-offs between these competing objectives explicit and adjustable through the sensitivity analysis on objective weights.

A key insight that the integrated approach reveals, which separate treatment would miss, is the interdependence between station location and fleet sizing. In a sequential approach, the facility location stage may open stations in locations that appear cost-efficient in isolation, but subsequently require an infeasibly large drone fleet to serve the assigned demand points within the operational time window. By jointly optimizing location and fleet sizing in the FLP, and then validating feasibility through the VRP, this study ensures that the resulting station network is not only coverage-optimal but also operationally executable within realistic drone constraints.

A spatial and demand analysis of the 84 unserved shelter posts reveals two key characteristics. First, from a demand perspective, 83 out of 84 unserved shelter posts (98.8%) have a drone demand of 1.0 kg or less, with a mean demand of 0.52 kg and a maximum of 1.10 kg. These are predominantly shelter posts whose needs were either already fully met at the time of data collection or had only minimal residual demand. Their total unmet demand amounts to only 43.64 kg, representing 0.5% of the total estimated demand across all 489 shelter posts. Second, from a spatial perspective, all 84 unserved shelter posts lie within 7.5 km of at least one opened drone station, meaning they are technically within the service range. Their non-assignment is therefore not a result of geographic inaccessibility but rather an outcome of the optimization trade-off, in which the model prioritizes shelter posts with higher demand under the equal-weight objective

configuration.

From a humanitarian perspective, even shelter posts with low demand represent real populations with residual needs that should not be overlooked. The model results suggest that these 84 shelter posts could potentially be served at marginal additional cost, given their proximity to existing stations. In practical deployment, these locations may be addressed through supplementary last-mile distribution mechanisms, such as ground-based delivery or manual logistics coordination, rather than relying solely on drone delivery. Furthermore, the sensitivity analysis results show that increasing the coverage weight α to 0.9 raises the number of served shelter posts to 487 out of 489 (99.6%), demonstrating that near-complete coverage is achievable within the proposed framework at the cost of a modest increase in daily operational expenditure. This suggests that the choice of objective weights should be informed by humanitarian priorities and available budget, and practitioners are encouraged to adjust α accordingly based on the urgency and equity requirements of the specific disaster response context.

To assess the operational feasibility of the routing solutions, we examine the trip and charging cycle structure of the deployed drones, using Station A as an illustrative example. At Station A, 6 drones are deployed across 29 trips in total. The drone with the longest operation time performs 5 delivery trips with 4 charging cycles between consecutive trips, yielding a total operation time of 697.7 minutes within the 720-minute daily limit. Of this, flight and service time accounts for 337.7 minutes, while charging time accounts for 360 minutes (4×90 minutes), representing approximately 51.6% of total operation time. Across all 6 drones at Station A, charging time accounts for between 51.6% and 58.9% of total daily operation time. While this confirms that battery charging consumes a substantial share of the operating day, a trade-off inherent to current battery-powered drone technology, all routing solutions across all eight stations remain feasible within the 720-minute daily operational limit, with maximum drone operation times ranging from 611.1 to 697.7 minutes. The high share of charging time is acknowledged as a limitation of the current framework; future research should explore fast-charging technologies, battery-swap mechanisms, or heterogeneous drone fleets with longer endurance to improve operational throughput.

An interesting direction for future research could also be to incorporate vulnerability indices and demand prioritization directly into the model formulation. For instance, shelter posts housing elderly populations, infants, pregnant women, or individuals with disabilities could be assigned higher priority weights in the coverage objective, ensuring that the optimization explicitly favors serving the most vulnerable populations regardless of their demand magnitude. Additionally, equity constraints could be introduced to guarantee a minimum service level for all shelter posts, preventing the systematic exclusion of low-demand locations that may nonetheless represent critical humanitarian needs.

From a methodological standpoint, this research contributes to the growing literature on humanitarian drone logistics in several ways. First, it presents an integrated FLP-VRP optimization framework based on real disaster data from the 2022 Cianjur earthquake, rather than relying solely

on synthetic benchmark instances. Second, the empirical evidence showing a meaningful efficiency gap between strategic fleet estimation and operational routing requirements provides new insight into the benefits of multi-level optimization in humanitarian systems. Third, the study introduces a modified SA acceptance mechanism that prioritizes drone minimization and service fulfillment, offering a practical heuristic design tailored to resource-constrained emergency environments. Together, these contributions advance both the theoretical modeling and practical implementation of drone humanitarian logistics.

The findings also yield several managerial implications for disaster response agencies and policymakers. The high coverage achieved with a limited number of drone stations suggests that strategic infrastructure planning can significantly enhance emergency logistics performance without requiring extensive investment. Furthermore, the demonstrated reduction in drone fleet size through routing optimization indicates that operational decision-support tools can meaningfully reduce costs and resource consumption. These insights are particularly relevant for archipelagic and disaster-prone countries such as Indonesia, where damaged transportation infrastructure frequently delays conventional aid distribution and where aerial logistics can provide a rapid, flexible alternative.

Despite these promising results, several limitations should be acknowledged. The optimization framework assumes deterministic conditions, excluding uncertainties such as weather variability, battery degradation, and dynamic demand evolution, all of which are critical in real disaster environments. Additionally, the study considers a single drone type and static routing structure, whereas real deployments may involve heterogeneous fleets and real-time decision adjustments. Future research should therefore explore stochastic and robust optimization approaches, integration with ground transportation or multimodal logistics, and the use of real-time data streams for adaptive routing. Expanding the framework to include multiple drone types, equity-based service objectives, and uncertainty-aware planning would further enhance its applicability for large-scale humanitarian operations.

6. CONCLUSION

This study proposed an integrated drone-based humanitarian logistics optimization framework that combines a multi-objective FLP with a VRP solved using a modified SA algorithm, evaluated using the 2022 Cianjur earthquake as a real disaster case study with demand estimated based on SPHERE Humanitarian Standards. The FLP results show that 8 strategically located drone stations achieve 82.8% service coverage across 405 of 489 shelter posts, with a weight coverage of 99.5% and a total daily cost of Rp 15,944,610. The VRP stage then reduces the upper-bound fleet estimate of 82 drones to 67 actually deployed, an 18.3% reduction equivalent to a daily saving of approximately Rp 2,821,575, demonstrating that the VRP is not merely an operational add-on but a critical cost-reduction mechanism. All routing solutions remain feasible within the 720-minute daily operational limit, and a spatial analysis of the 84 unserved shelter posts confirms that non-assignment reflects an opti-

mization trade-off rather than a geographic barrier, with their total unmet demand amounting to only 0.5% of total estimated demand. The sensitivity analysis further shows that near-complete coverage of 99.6% is achievable by adjusting the coverage weight α to 0.9, confirming that the objective weights serve as a practical policy lever for balancing coverage, cost, and equity in disaster response contexts. Methodologically, this research contributes an integrated FLP–VRP framework based on real disaster data with a modified SA acceptance strategy that prioritizes fleet minimization and service fulfillment. The results highlight the practical potential of drone logistics optimized for disaster relief distribution, particularly in regions with disrupted ground transportation. Several limitations remain, including the model’s deterministic assumptions, single drone type, and static routing structure, which future research should address through stochastic or robust optimization, heterogeneous fleets, multi-modal integration, and real-time dynamic routing. Overall, the study demonstrates that integrated strategic–operational optimization can significantly improve the coverage, efficiency, and feasibility of drone-based humanitarian logistics, supporting the broader adoption of technology-enabled decision support in emergency response operations.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

DATA AVAILABILITY STATEMENTS

The data used in this study were obtained from publicly available sources provided by the National Disaster Management Agency of Indonesia (BNPB). The processed datasets and model implementation files generated during the study are available at <https://osf.io/wkbm5>.

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