

Article

A Two-Phase Optimization Framework for UAV Communication in Pickup-and-Delivery Missions

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Abstract

Unmanned aerial vehicles (UAVs) are increasingly employed for parcel logistics while simultaneously serving as aerial communication platforms. However, jointly optimizing pickup-and-delivery operations and wireless communication raises a large-scale mixed-integer nonlinear programming problem due to the coupling of binary logistics decisions, trajectory planning, time allocation, user scheduling, and transmit-power control. This paper proposes a two-phase optimization framework that enables a dual-purpose UAV mission by jointly considering parcel pickup-and-delivery and downlink communication within a single framework. The key strength of the proposed approach is that it separates the logistics-dominated delivery stage from the communication-oriented service stage, thereby reducing the difficulty of directly handling the highly coupled MINLP while exploiting the residual mission time for communication enhancement. In Phase 1, a pickup-and-delivery optimization problem is formulated to minimize the delivery completion time by determining the UAV trajectory, time-slot lengths, and item handling sequence, where the binary pickup/drop-off decisions are relaxed and progressively enforced through a penalty convex–concave procedure. In Phase 2, communication performance is enhanced by optimizing user scheduling and transmit power over the entire mission horizon, together with residual flight trajectory refinement after delivery completion using successive convex approximation and block coordinate descent. Simulation results show that the proposed algorithm substantially improves the minimum average spectral efficiency among ground nodes while achieving early completion of logistics tasks. Compared with baseline strategies, the proposed method delivers consistent performance gains under various system parameters. In particular, it improves the minimum average spectral efficiency by up to 15% compared with the baseline that removes the proposed post-delivery trajectory refinement, demonstrating the benefit of exploiting the residual flight trajectory for communication enhancement after delivery completion.

Keywords: convex optimization; unmanned aerial vehicle; pickup-and-delivery; communication; trajectory design



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1. Introduction

Unmanned aerial vehicles (UAVs) have become an essential component of next-generation smart logistics and wireless connectivity, owing to their mobility, flexible deployment, and wide coverage capability [1,2]. Recent advances in autonomous aerial delivery systems enable UAVs to efficiently pick up and deliver multiple items across large regions, making them promising alternatives to conventional ground-based logistics. At the same time, UAVs are increasingly envisioned as aerial communication platforms that can assist or

complement terrestrial networks, supporting reliable downlink services for ground nodes (GNs) in remote or highly dynamic environments. Such UAV-assisted links can provide rapid and flexible connectivity in rural or disaster-stricken areas, as well as in temporary hotspots with sharply increased traffic demand, where existing terrestrial infrastructure is sparse, damaged, or temporarily overloaded [3–5]. These emerging trends signify that future UAVs will operate as multi-purpose agents, simultaneously executing logistics and communication tasks within a single mission.

Extensive research has been conducted on UAV-enabled communications [6–18] and UAV-assisted logistics [19–23]. In wireless communications, several works have designed UAV trajectories and resource allocation to improve communication quality. For example, Refs. [6,7] jointly optimized UAV trajectory and communication scheduling for multi-UAV wireless networks, while [8] developed a hybrid offline–online trajectory and resource design for UAV-enabled data harvesting. More recently, Ref. [9] considered UAV trajectory and communication-resource optimization under no-fly-zone constraints. Another research stream has viewed the UAV from an energy-efficiency perspective, where UAV propulsion energy, communication requirements, and mission completion costs are jointly considered [10,11]. Furthermore, UAV-assisted wireless-powered communication has been studied by jointly optimizing UAV trajectory, energy transfer, and communication resource allocation to support battery-limited GNs [12–14]. A recent study also investigated information freshness and wireless-powered UAV communication by jointly designing age of information (AoI)-minimal clustering, transmission, and trajectory control for UAV-assisted wireless-powered communication networks [15]. In addition, secure UAV communication has been addressed by exploiting UAV mobility and resource allocation to mitigate eavesdropping threats [16]. Recent studies have also investigated learning-based UAV communication approaches. In particular, deep reinforcement learning (DRL)-based trajectory optimization and resource-allocation methods were developed for online decision-making under time-varying channel conditions, user demands, or network topology [17]. In addition, hybrid optimization–learning methods were explored to combine model-based optimization with learning-assisted adaptation in UAV communication systems [18]. In the logistics-oriented research domain, Ref. [19] studied stochastic and demand-driven task scheduling for UAV-based on-demand delivery systems. The work in [20] proposed 3D multi-trajectory and pickup planning to minimize delivery time under payload or weight constraints, while [21] investigated trajectory and pickup coordination under no-fly-zone constraints. Beyond single-UAV operation, multi-UAV logistics systems have also been studied, including swarm-based delivery platforms and energy-balanced pickup-and-delivery assignment [22,23]. Overall, the above studies provide important foundations for UAV communication and UAV logistics. However, communication-oriented works, including recent learning-based approaches, mainly optimize trajectory and radio resources without explicitly modeling item-handling decisions, whereas logistics-oriented works focus on delivery operations without jointly optimizing downlink communication service to GNs. This motivates the integrated pickup-and-delivery communication framework considered in this paper.

When logistics and communication coexist within the same UAV mission, the resulting joint operation introduces far more complex coupling than addressed in prior works. The UAV's trajectory and time allocation must simultaneously reflect the spatial distribution of pickup-and-delivery zones and the channel-dependent communication requirements of GNs. Moreover, strict physical and operational constraints, such as payload capacity, altitude regulations during item handling, binary pickup/drop-off decisions, and flight-time budgets, must be satisfied without compromising communication performance. Under these intertwined influences, the joint optimization problem becomes a

large-scale mixed-integer nonlinear program (MINLP) containing highly coupled variables, including trajectory, delivery sequencing, time-slot allocation, scheduling indicators, and transmit power. Directly solving such a unified formulation is computationally prohibitive and often leads to feasibility-dominated convergence, which prioritizes completion of logistics tasks at the expense of communication performance. To resolve this challenge, this paper proposes a two-phase optimization framework that decouples the logistics-dominated and communication-dominated stages of the mission. In Phase 1, a feasible and time-efficient pickup-and-delivery plan is generated under operational and spatial constraints to complete delivery tasks as early as possible within the mission horizon. In Phase 2, the pickup/drop-off decisions and the UAV trajectory up to the final delivery slot are fixed from Phase 1, and communication performance is enhanced by optimizing GN scheduling and transmit power over the entire mission horizon while further refining the UAV trajectory only over the post-delivery segment. The resulting Phase-2 optimization aims to maximize the minimum average spectral efficiency (SE) among GNs. The major contributions of this work are summarized as follows: (1) We establish a unified model for a dual-purpose UAV that simultaneously performs parcel pickup-and-delivery and downlink communication while incorporating all relevant operational, spatial, and communication constraints. (2) We develop a two-phase optimization method that isolates the combinatorial delivery-related feasibility issues from the communication-oriented performance improvement phase, enabling efficient and scalable optimization. (3) We develop a penalty convex–concave procedure (PCCP)-driven successive convex approximation (SCA) algorithm for Phase 1, where the relaxed pickup/drop-off variables are progressively driven toward binary values and the nonconvex service-zone constraints are converted into convex surrogate constraints. For Phase 2, we design a block coordinate descent (BCD)-based SCA algorithm that decomposes the communication optimization into scheduling, transmit-power, and residual trajectory subproblems, enabling efficient communication-oriented optimization after delivery completion. (4) Simulation results demonstrate that the proposed framework consistently outperforms baseline methods across various system parameters by completing delivery tasks early and utilizing the remaining mission time to significantly enhance communication services.

The remainder of this paper is structured as follows. Section 2 presents the system model and problem formulation. Section 3 describes the proposed two-phase optimization framework. Section 4 provides simulation results and comparisons with baseline schemes. Section 5 concludes the paper.

2. System Model and Problem Statement

Figure 1 presents a system model of UAV communication with pickup-and-delivery missions. A rotary-wing UAV starts from an initial point denoted by $\mathbf{c}^{\text{org}}$, visits K pickup locations to collect individual items with weights w_k , delivers them to their designated delivery zones, and eventually arrives at a terminal point $\mathbf{c}^{\text{dst}}$. The entire mission must be completed within a total flight duration T , which is partitioned into N time intervals. Unlike fixed-slot models, the duration of each interval, $\delta[n] \geq 0$, is adjustable and satisfies $T = \sum_{n=1}^N \delta[n]$, while the slot count N remains constant [20].

During slot $n \in \mathcal{N} = \{1, 2, \dots, N\}$, the UAV's 3D position is represented by $\mathbf{c}[n] = (\mathbf{q}[n], z[n])$, where $\mathbf{q}[n] = (x[n], y[n])$ denotes its horizontal position and $z[n]$ represents its altitude. The UAV's motion is governed by a maximum speed limit $V_{\max}$, implying that the displacement between two consecutive positions cannot exceed the maximum distance travelable within $\delta[n]$. This yields the following mobility constraints:

$$\mathbf{c}[0] = \mathbf{c}^{\text{org}}, \quad \mathbf{c}[N] = \mathbf{c}^{\text{dst}}, \quad (1)$$

$$\|\mathbf{c}[n] - \mathbf{c}[n-1]\| \leq \delta[n] V_{\max}, \quad \forall n. \quad (2)$$

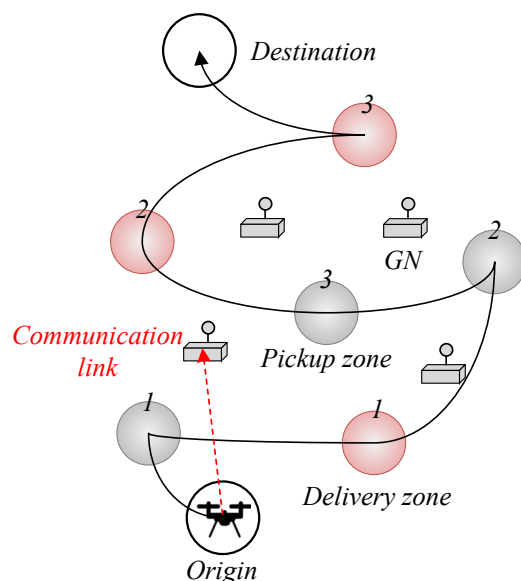


Figure 1. System model of UAV communication with $K = 3$ pickup-and-delivery missions.

Let $\alpha_k[n]$ and $\beta_k[n]$ denote binary decision variables that specify when the UAV collects and releases item $k \in \mathcal{K} = \{1, 2, \dots, K\}$, respectively. In particular, $\alpha_k[n] = 1$ indicates that item k is taken onboard during slot n , whereas $\beta_k[n] = 1$ signifies that it is delivered at that slot; both variables are zero otherwise. Then, the pickup–delivery operations must satisfy the following feasibility conditions:

$$\{\alpha_k[n], \beta_k[n]\} \in \{0, 1\}, \quad \forall k, n, \quad (3)$$

$$\sum_{n=1}^N \alpha_k[n] \leq 1, \quad \forall k, \quad (4)$$

$$\sum_{n=1}^N \beta_k[n] \leq 1, \quad \forall k, \quad (5)$$

$$\sum_{k=1}^K (\alpha_k[n] + \beta_k[n]) \leq 1, \quad \forall n, \quad (6)$$

$$\sum_{j=2}^n \beta_k[j] \leq \sum_{j=1}^{n-1} \alpha_k[j], \quad \forall k, n \neq 1, \quad (7)$$

$$W[n] = \sum_{k=1}^K w_k \left(\sum_{j=1}^n \alpha_k[j] - \sum_{j=1}^n \beta_k[j] \right) \leq W_{\max}, \quad \forall n, \quad (8)$$

$$\sum_{k=1}^K \sum_{n=1}^N \beta_k[n] \geq K. \quad (9)$$

Constraint (3) defines the binary decision variables $\alpha_k[n]$ and $\beta_k[n]$. Constraints (4) and (5) ensure that each item can be picked up and delivered at most once over the mission duration, preventing multiple or repeated pickup and drop-off actions for the same item. Constraint (6) restricts the UAV to performing at most one operation, either a pickup or a drop-off, within each time slot, reflecting its physical limitation that it cannot handle multiple items simultaneously. Constraint (7) enforces the logical consistency between pickup-and-delivery actions by ensuring that no item can be delivered before it has been picked up. Constraint (8) maintains payload feasibility by ensuring that the total

onboard weight $W[n]$ never exceeds the UAV's maximum payload capacity $W_{\max}$. Finally, constraint (9) ensures mission completeness by requiring that all K items be successfully delivered within the mission period.

During normal flight, the UAV remains at the predetermined altitude H , whereas altitude reduction is allowed solely for item-handling operations. Consequently, the altitude constraint is written as

$$\left(1 - \sum_{k=1}^K (\alpha_k[n] + \beta_k[n])\right) H \leq z[n] \leq H, \forall n. \quad (10)$$

To execute item pickup or drop-off, the UAV must remain inside the designated service zone associated with each item. For item k , the pickup zone is modeled as a circular region centered at $\mathbf{c}_k = (\mathbf{q}_k, z_k)$ with radius R_k , while the delivery zone is defined as a circular region centered at $\hat{\mathbf{c}}_k = (\hat{\mathbf{q}}_k, \hat{z}_k)$ with radius $\hat{R}_k$. These regions specify the allowable spatial tolerance for safe approach and manipulation of the item. The UAV must stay within the relevant zone throughout not only the pickup or drop-off instant but also the entire descent and ascent phases. Based on this requirement, the spatial constraints can be expressed as

$$\alpha_k[n] \|\mathbf{c}[n] - \mathbf{c}_k\|^2 \leq R_k^2, \forall k, n \neq N, \quad (11)$$

$$\alpha_k[n] \|\mathbf{q}[j] - \mathbf{q}_k\|^2 \leq R_k^2, \forall k, n \neq N, j \in \{n-1, n+1\}, \quad (12)$$

$$\beta_k[n] \|\mathbf{c}[n] - \hat{\mathbf{c}}_k\|^2 \leq \hat{R}_k^2, \forall k, n \neq N, \quad (13)$$

$$\beta_k[n] \|\mathbf{q}[j] - \hat{\mathbf{q}}_k\|^2 \leq \hat{R}_k^2, \forall k, n \neq N, j \in \{n-1, n+1\}. \quad (14)$$

These spatial constraints ensure that the UAV descends below H only within the designated pickup or delivery zones, thereby maintaining consistency with the altitude restriction and preventing unintended descent during flight.

To quantify when each item is fully delivered, we define the delivery completion index for item k as

$$n_k = \sum_{n=1}^N n \beta_k[n], \forall k. \quad (15)$$

Since $\beta_k[n] = 1$ only at the time slot in which item k is dropped off, n_k uniquely identifies the delivery time slot of that item. Based on this index, the actual physical delivery time for item k is computed as

$$\tau_k = \sum_{n=1}^{n_k} \delta[n], \forall k, \quad (16)$$

which represents the cumulative time elapsed from the mission start until its drop-off slot. Finally, the overall delivery completion time is characterized as

$$T_D = \max_k \tau_k, \quad (17)$$

which captures the latest delivery among all items.

For communication operations, let $s_l[n]$ denote a binary scheduling indicator that specifies whether GN $l \in \mathcal{L} = \{1, 2, \dots, L\}$ is selected to receive downlink transmission from the UAV in time slot n . In particular, $s_l[n] = 1$ means that the UAV transmits data to GN l during slot n , whereas $s_l[n] = 0$ indicates that the GN is not scheduled. Since the UAV serves only one GN in each slot, the scheduling constraints are expressed as

$$s_l[n] \in \{0, 1\}, \forall l, n, \quad (18)$$

$$\sum_{l=1}^L s_l[n] \leq 1, \forall n. \quad (19)$$

The UAV transmits with power $p[n]$ in slot n , subject to peak and average power limitations:

$$0 \leq p[n] \leq P_{\text{peak}}, \forall n, \quad (20)$$

$$\frac{1}{N} \sum_{n=1}^N p[n] \leq P_{\text{avg}}, \quad (21)$$

where P_{peak} and P_{avg} represent peak and average power budgets, respectively.

Under LoS propagation [6,12–14], the channel power gain between the UAV and GN l , located at $\mathbf{c}_l$, during time slot n is represented by

$$h_l[n] = \frac{\mu_0}{\|\mathbf{c}[n] - \mathbf{c}_l\|^2}, \forall l, n, \quad (22)$$

where μ_0 denotes the reference channel gain measured at a distance of 1 m. The corresponding downlink SE of GN l in slot n is

$$\begin{aligned} r_l[n] &= \log_2 \left(1 + \frac{h_l[n]p[n]}{\sigma^2} \right) \\ &= \log_2 \left(1 + \frac{\mu_0 p[n]}{\sigma^2 \|\mathbf{c}[n] - \mathbf{c}_l\|^2} \right), \end{aligned} \quad (23)$$

where σ^2 is the noise power. The average SE over the entire flight period is then given by

$$R_l = \frac{1}{T} \sum_{n=1}^N s_l[n] \delta[n] r_l[n], \forall l. \quad (24)$$

In this study, the goal is to maximize the minimum average SE among all GNs, which is defined as $\eta = \min_{l \in \mathcal{L}} R_l$, while ensuring the delivery of all items within a mission time T . The optimization is jointly performed over the pickup and drop-off assignment variables $\alpha \triangleq \{\alpha_k[n], \forall k, n\}$ and $\beta \triangleq \{\beta_k[n], \forall k, n\}$, the time-slot lengths $\delta \triangleq \{\delta[n], \forall n\}$, the scheduling indicators $s \triangleq \{s_l[n], \forall l, n\}$, the transmit power $p \triangleq \{p[n], \forall n\}$, and the UAV trajectory $c \triangleq \{\mathbf{c}[n], \forall n\}$. Using this definition, the joint pickup–delivery and communication optimization problem is formulated as

$$\begin{aligned} \text{(P0):} \quad & \max_{\alpha, \beta, \delta, s, p, c, \eta} \quad \eta \\ & \text{subject to} \quad R_l \geq \eta, \forall l, \\ & \quad \quad \quad (1)–(14), (18)–(21). \end{aligned} \quad (25)$$

Problem (P0) is a challenging MINLP because the pickup and drop-off assignment variables (α and β) and the scheduling indicators (s) are binary, as defined in (3) and (18). In addition, the UAV trajectory, time-slot lengths, scheduling indicators, and transmit power are tightly coupled through the mobility constraints and the average SE constraints. The service-zone constraints in (11)–(14) are also nonconvex because they involve products between binary operation indicators and distance-dependent trajectory terms, while the communication constraint in (25) is nonconvex due to the nonlinear dependence of the SE on the UAV–GN distance and transmit power. These coupled integer and nonconvex

structures make the direct solution of (P0) computationally prohibitive and analytically intractable. Furthermore, the pickup-and-delivery constraints form a highly restricted feasible region, so a direct unified solution can be dominated by delivery feasibility and may leave only limited room for communication-performance improvement. These difficulties motivate the proposed two-phase optimization framework described in the next section.

3. Proposed Optimization Framework

The unified formulation (P0) jointly optimizes delivery operations and communication performance, but solving it directly is challenging due to both variable-level coupling and mission-level conflict. Specifically, the pickup-and-delivery constraints, including binary item-handling decisions and spatial service-zone constraints, form a highly restricted feasible region. Thus, trajectory adjustments that may improve communication performance can easily violate logistics feasibility, leaving the solver with only limited feasible directions to increase η . As a result, a direct unified solution may be dominated by delivery feasibility and may converge to a solution that satisfies the logistics requirements without sufficiently improving the communication rate. Motivated by this difficulty, we decompose the original MINLP into two connected phases according to the dominant mission objective. This two-phase division is not intended to replace variable-wise subproblem decomposition; rather, it provides a mission-level decomposition that separates the logistics-dominated stage from the communication-dominated stage. In Phase 1, the UAV determines the pickup/drop-off sequence, time-slot lengths, and trajectory to complete all deliveries as early as possible. The resulting delivery completion time T_D , last delivery slot η_D , and trajectory up to the final delivery are then passed to Phase 2. In Phase 2, the pickup/drop-off decisions and the UAV trajectory up to the final delivery slot are fixed from Phase 1. Based on this partially fixed mission structure, GN scheduling and transmit power are optimized over the entire mission horizon, while the UAV trajectory is further optimized only over the post-delivery segment. Within this phase, the communication problem is further decomposed into scheduling, transmit-power, and trajectory subproblems and solved using a BCD-based SCA procedure. Thus, the proposed method can be interpreted as a hierarchical decomposition approach, where Phase 1 provides a feasible logistics foundation and Phase 2 exploits the whole mission horizon for scheduling and power control, while using the residual post-delivery mobility resources for trajectory refinement. Algorithmically, the key contribution is that the binary and spatial nonconvexity of the delivery phase is handled through PCCP-based relaxation and SCA-based convexification, while the residual communication phase is solved through BCD-based variable decomposition. This decomposition also introduces a sub-optimality trade-off. Since Phase 1 focuses on completing the pickup-and-delivery mission, the UAV trajectory and time-slot lengths up to the final delivery slot are determined primarily by logistics considerations. Although GN scheduling and transmit power are optimized over the entire mission horizon in Phase 2 and the post-delivery trajectory is further refined for communication enhancement, the pre-delivery trajectory is not directly optimized from a communication-performance perspective. Therefore, the communication performance during the delivery phase may still be lower than that of a fully joint logistics–communication optimization. Nevertheless, this trade-off is accepted to make the original problem more tractable under the strict delivery constraints. Incorporating a communication-aware term into the Phase-1 objective is a possible future extension. Such an extension could guide the delivery-phase trajectory and time-slot allocation to partially account for communication performance, thereby better balancing delivery efficiency and communication service quality while preserving logistics feasibility.

3.1. Pickup-and-Delivery Optimization

The objective of the first phase is to determine a feasible and time-efficient pickup-and-delivery plan that satisfies all operational and spatial constraints while minimizing the actual delivery completion time T_D and the latest delivery index $\eta_D = \max_{k \in \mathcal{K}} n_k$. Since T_D is measured in seconds whereas η_D is a slot index, we introduce the delivery-index weighting coefficient ω to convert the index-related term into the same time-related scale. The index η_D indicates the final time slot in which any delivery occurs; hence, reducing it shortens the portion of the slot sequence occupied by logistics operations and leaves more residual slots for communication optimization in Phase 2. To incorporate this design consideration, the first-phase problem is formulated as

$$\begin{aligned} \text{(P1-1): } \quad & \min_{\alpha, \beta, \delta, c, \eta_D} T_D + \omega \eta_D \\ & \text{subject to } \eta_D \geq n_k, \forall k, \\ & \quad (1)-(14). \end{aligned} \quad (26)$$

To incorporate the binary decisions of $\alpha_k[n]$ and $\beta_k[n]$ in (3), we first relax them to continuous variables and then impose their discreteness through nonlinear equality constraints:

$$\{\alpha_k[n], \beta_k[n]\} \in [0, 1], \forall k, n, \quad (27)$$

$$\alpha_k[n](1 - \alpha_k[n]) \leq 0, \forall k, n, \quad (28)$$

$$\beta_k[n](1 - \beta_k[n]) \leq 0, \forall k, n. \quad (29)$$

Here, (27) provides a convex relaxation, whereas (28) and (29) enforce binary feasibility. These constraints are nonconvex because the terms $\alpha_k[n](1 - \alpha_k[n])$ and $\beta_k[n](1 - \beta_k[n])$ are concave over the interval $[0, 1]$. Enforcing these concave inequalities makes the binary feasible region highly restricted and nonconvex, which significantly increases the difficulty of solving the problem directly.

To enable tractable optimization, we approximate the concave expressions in (28) and (29) with their first-order Taylor upper bounds at the values obtained from the previous SCA iteration. Following the PCCP [24], nonnegative slack variables $\rho_k[n] \geq 0$ and $\kappa_k[n] \geq 0$ are introduced to temporarily relax the binary condition and progressively tighten it during iterations. The resulting convex surrogate constraints become

$$(\tilde{\alpha}_k[n])^2 + \alpha_k[n](1 - 2\tilde{\alpha}_k[n]) \leq \rho_k[n], \forall k, n, \quad (30)$$

$$(\tilde{\beta}_k[n])^2 + \beta_k[n](1 - 2\tilde{\beta}_k[n]) \leq \kappa_k[n], \forall k, n, \quad (31)$$

where $\tilde{\alpha}_k[n]$ and $\tilde{\beta}_k[n]$ denote the values obtained in the previous iteration. These convexified forms ensure that the optimization remains computationally manageable while gradually restoring the binary nature of $\alpha_k[n]$ and $\beta_k[n]$.

The pickup zone constraint (11) contains the nonconvex coupling term $\alpha_k[n]\|\mathbf{c}[n] - \mathbf{c}_k\|^2$, which makes the feasible set difficult to handle directly. To obtain a tractable form, we first rewrite (11) as

$$\alpha_k[n] \leq \frac{R_k^2 + \varepsilon}{\|\mathbf{c}[n] - \mathbf{c}_k\|^2 + \varepsilon}, \quad (32)$$

where $\varepsilon > 0$ is a constant introduced to avoid division by zero. Although this reformulation still results in a nonconvex constraint, the right-hand side (RHS) becomes a convex function with respect to the term $\|\mathbf{c}[n] - \mathbf{c}_k\|^2 + \varepsilon$. This allows us to obtain a tractable convex

surrogate by applying a first-order Taylor at a local point $\tilde{\mathbf{c}}[n]$, which leads to the following linearized constraint:

$$\alpha_k[n] \leq \frac{R_k^2 + \varepsilon}{\|\tilde{\mathbf{c}}[n] - \mathbf{c}_k\|^2 + \varepsilon} - \frac{R_k^2 + \varepsilon}{(\|\tilde{\mathbf{c}}[n] - \mathbf{c}_k\|^2 + \varepsilon)^2} \left(\|\mathbf{c}[n] - \mathbf{c}_k\|^2 - \|\tilde{\mathbf{c}}[n] - \mathbf{c}_k\|^2 \right), \quad \forall k, n \neq N. \quad (33)$$

A similar convexification is applied to (12)–(14), yielding

$$\alpha_k[n] \leq \frac{R_k^2 + \varepsilon}{\|\tilde{\mathbf{q}}[j] - \mathbf{q}_k\|^2 + \varepsilon} - \frac{R_k^2 + \varepsilon}{(\|\tilde{\mathbf{q}}[j] - \mathbf{q}_k\|^2 + \varepsilon)^2} \left(\|\mathbf{q}[j] - \mathbf{q}_k\|^2 - \|\tilde{\mathbf{q}}[j] - \mathbf{q}_k\|^2 \right), \quad \forall k, n \neq N, j \in \{n-1, n+1\}, \quad (34)$$

$$\beta_k[n] \leq \frac{\hat{R}_k^2 + \varepsilon}{\|\tilde{\mathbf{c}}[n] - \hat{\mathbf{c}}_k\|^2 + \varepsilon} - \frac{\hat{R}_k^2 + \varepsilon}{(\|\tilde{\mathbf{c}}[n] - \hat{\mathbf{c}}_k\|^2 + \varepsilon)^2} \left(\|\mathbf{c}[n] - \hat{\mathbf{c}}_k\|^2 - \|\tilde{\mathbf{c}}[n] - \hat{\mathbf{c}}_k\|^2 \right), \quad \forall k, n \neq N, \quad (35)$$

$$\beta_k[n] \leq \frac{\hat{R}_k^2 + \varepsilon}{\|\tilde{\mathbf{q}}[j] - \hat{\mathbf{q}}_k\|^2 + \varepsilon} - \frac{\hat{R}_k^2 + \varepsilon}{(\|\tilde{\mathbf{q}}[j] - \hat{\mathbf{q}}_k\|^2 + \varepsilon)^2} \left(\|\mathbf{q}[j] - \hat{\mathbf{q}}_k\|^2 - \|\tilde{\mathbf{q}}[j] - \hat{\mathbf{q}}_k\|^2 \right), \quad \forall k, n \neq N, j \in \{n-1, n+1\}, \quad (36)$$

where $\tilde{\mathbf{q}}[j]$ denotes the horizontal position of the UAV at time slot j obtained from the previous SCA iteration. These surrogate constraints are convex and thus compatible with SCA-based iterative optimization.

Using the relaxed and convexified constraints above, the problem (P1-1) is reformulated as the following convex optimization problem:

$$\begin{aligned} \text{(P1-2):} \quad & \min_{\alpha, \beta, \delta, \mathbf{c}, \rho, \kappa, \eta_D} T_D + \omega \eta_D + \nu \mathcal{P}(\rho, \kappa) \\ & \text{subject to} \quad (1), (2), (4) - (10), (26), (27), (30), (31), (33) - (36), \end{aligned}$$

where the penalty function is defined as $\mathcal{P}(\rho, \kappa) = \sum_{k=1}^K \sum_{n=1}^N (\rho_k[n] + \kappa_k[n])$ with $\rho \triangleq \{\rho_k[n], \forall k, n\}$ and $\kappa \triangleq \{\kappa_k[n], \forall k, n\}$. This term penalizes deviations from the binary nature of the pickup and drop-off assignment variables, thereby pushing $\alpha_k[n]$ and $\beta_k[n]$ toward $\{0, 1\}$. The weighting parameter $\nu > 0$ balances the primary objective and the penalty in problem (P1-2). A small ν allows for temporary nonzero slack variables, yielding relaxed values of $\alpha_k[n]$ and $\beta_k[n]$. As ν increases, the penalty dominates and drives $\rho_k[n]$ and $\kappa_k[n]$ toward zero, gradually enforcing binary feasibility. This continuation approach enables a smooth shift from the relaxed formulation to a binary-compliant solution [24].

By solving this problem, the UAV obtains a feasible trajectory that completes all item deliveries as early as possible within the mission horizon. Importantly, this phase isolates the highly restrictive combinatorial and nonconvex elements that would otherwise dominate the unified formulation. The resulting trajectory and time allocation provide a structured and feasible basis on which the subsequent communication optimization can operate more effectively.

3.2. Communication Optimization

Before optimizing communication performance, we fix the pickup and drop-off assignment variables α and β obtained from problem (P1-2). In addition, the UAV trajectory $\mathbf{c}$ is fixed up to the time slot when the UAV reaches the final delivery zone where the last parcel is delivered. After arriving at this zone, the remaining mission time $T - T_D$ is evenly divided into the remaining time slots, $N - \eta_D$, which yields a fixed time-slot length $\delta[n] = \frac{T - T_D}{N - \eta_D}$ for $n > \eta_D$. This uniform allocation is not claimed to be globally optimal; rather, it is adopted to keep the Phase 2 communication optimization tractable. If the residual slot lengths are also optimized, they become coupled with scheduling through

$s_l[n]\delta[n]r_l[n]$ and with trajectory through $\|\mathbf{c}[n] - \mathbf{c}[n-1]\| \leq \delta[n]V_{\max}$, which increases the nonconvexity of the problem. Therefore, we fix the residual slot lengths and optimize GN scheduling and transmit power over the entire mission horizon, while optimizing the UAV trajectory only over the post-delivery segment. Joint residual time allocation is an interesting extension and is left as future work.

Under these fixed variables, the goal of the second phase is to maximize the minimum average SE among all GNs, which is defined as $\eta_C = \min_{l \in \mathcal{L}} R_l$, by optimizing the scheduling indicators $\mathbf{s} \triangleq \{s_l[n], \forall l, n\}$, the transmit power $\mathbf{p} \triangleq \{p[n], \forall n\}$, and the UAV trajectory $\mathbf{c} \triangleq \{\mathbf{c}[n], \forall n > \eta_D\}$. Here, the scheduling indicators and transmit power are optimized over the entire mission horizon, whereas the UAV trajectory is optimized only for the post-delivery segment. The resulting problem is formulated as

$$\begin{aligned} \text{(P2-1): } & \max_{\mathbf{s}, \mathbf{p}, \mathbf{c}, \eta_C} \eta_C \\ & \text{subject to } R_l \geq \eta_C, \forall l, \\ & \quad (1), (2), (18)–(21). \end{aligned} \quad (37)$$

To tackle the nonconvexity of (P2-1), we decompose it into three manageable subproblems, each associated with a different group of optimization variables. For every subproblem, we employ an SCA-based reformulation to obtain a tractable convex approximation. These convexified subproblems are then addressed successively using a BCD-based iterative procedure. The solution process for each subproblem is summarized as follows.

3.2.1. Optimization of Scheduling Indicator

By relaxing $s_l[n]$ to take values in $[0, 1]$, the scheduling subproblem for fixed $\mathbf{p}$ and $\mathbf{c}$ is

$$\begin{aligned} \text{(SP2-1): } & \max_{\mathbf{s}, \eta_C} \eta_C \\ & \text{s. t. } 0 \leq s_l[n] \leq 1, \forall l, n, \\ & \quad (19), (37). \end{aligned} \quad (38)$$

This subproblem is a linear program and can be efficiently solved using CVX. Unlike the pickup/drop-off variables α and β , the relaxed scheduling variable $s_l[n] \in [0, 1]$ can be interpreted as the portion of slot n assigned to GN l . This is valid because the UAV trajectory, time-slot length, and transmit power are fixed in the scheduling subproblem, so the achievable rate $r_l[n]$ is fixed within each slot. Accordingly, a fractional scheduling value can be implemented by dividing the slot into smaller sub-slots and serving each GN for the corresponding fraction of the slot duration. Since the average SE depends on the accumulated served time, this time-sharing implementation preserves the same average SE as the relaxed solution. Therefore, the fractional scheduling solution can be implemented as an equivalent binary schedule by sufficiently fine sub-slot division, without changing the achieved average SE [6].

3.2.2. Optimization of Transmit Power

For fixed $\mathbf{s}$ and $\mathbf{c}$, the subproblem of optimizing $\mathbf{p}$ can be formulated as

$$\begin{aligned} \text{(SP2-2): } & \max_{\mathbf{p}, \eta_C} \eta_C \\ & \text{s. t. } (20), (21), (37). \end{aligned}$$

Since (SP2-2) is a convex problem with respect to $\mathbf{p}$, it can be efficiently addressed using standard convex optimization tools.

3.2.3. Optimization of Trajectory

For fixed s and p , the subproblem of optimizing c is given by

$$\begin{aligned} \text{(SP2-3): } & \max_{c, \eta_C} \eta_C \\ & \text{s. t. } (1), (2), (37). \end{aligned}$$

To convexify constraint (37), we exploit the fact that $r_l[n]$ is a convex function with respect to $\|c[n] - c_l\|^2$. Using this property, we linearize $r_l[n]$ via a first-order Taylor approximation around the point $\tilde{c}[n]$, yielding the following convex lower bound:

$$\begin{aligned} r_l[n] & \geq -\tilde{A}_l[n](\|c[n] - c_l\|^2 - \|\tilde{c}[n] - c_l\|^2) + \log_2\left(1 + \frac{\mu_0 p[n]}{\sigma^2 \|\tilde{c}[n] - c_l\|^2}\right) \\ & \triangleq \bar{r}_l[n], \end{aligned} \quad (39)$$

where $\tilde{A}_l[n]$ is given by

$$\tilde{A}_l[n] = \frac{\log_2(e) \mu_0 p[n]}{\mu_0 p[n] \|\tilde{c}[n] - c_l\|^2 + \sigma^2 \|\tilde{c}[n] - c_l\|^4}. \quad (40)$$

By substituting $r_l[n]$ with its surrogate $\bar{r}_l[n]$, the nonconvex constraint (37) is converted into the following convex inequality:

$$\bar{R}_l = \frac{1}{T} \sum_{n=1}^N s_l[n] \delta[n] \bar{r}_l[n] \geq \eta_C, \quad \forall l. \quad (41)$$

Accordingly, the trajectory subproblem is reformulated into the following convex problem:

$$\begin{aligned} \text{(SP2-3'): } & \max_{c, \eta_C} \eta_C \\ & \text{subject to } (1), (2), (41). \end{aligned}$$

3.3. Proposed Algorithm

The subproblems (P1-2), (SP2-1), (SP2-2), and (SP2-3') are all convex with respect to their corresponding optimization variables. Each subproblem can therefore be efficiently solved using standard convex optimization tools within an iterative framework [25,26]. The overall solution procedure is summarized in Algorithm 1.

The convergence of Algorithm 1 follows from the standard PCCP/SCA and BCD principles. In Phase 1, the nonconvex binary and service-zone constraints are replaced by convex surrogate constraints constructed at the previous iterate, and the slack variables are gradually suppressed by the bounded penalty update. Thus, the Phase-1 objective sequence converges to a finite value under the PCCP/SCA framework. In Phase 2, the scheduling, transmit-power, and trajectory blocks are updated successively while fixing the other variables. Each block update does not decrease the minimum average SE, and the objective is upper-bounded by the finite power budget and mission duration. Therefore, the Phase-2 objective sequence is monotonic and bounded, and hence convergent. Consequently, the proposed algorithm produces a convergent locally feasible solution under the adopted PCCP/SCA and BCD framework.

The computational complexity of Algorithm 1 can be obtained by separately analyzing the two iterative loops. In Phase 1, the dominant variables are the pickup/drop-off-related variables ($\alpha_k[n]$ and $\beta_k[n]$) and their associated slack variables ($\rho_k[n]$ and $\kappa_k[n]$), whose total dimension scales with NK . The trajectory and time-slot variables scale with N and therefore appear as lower-order terms compared with the delivery-related variables. Hence,

the effective problem size of each convexified Phase-1 subproblem is of order NK . Based on the standard worst-case complexity of interior-point methods, solving each Phase-1 convex subproblem requires $\mathcal{O}((NK)^{3.5} \log(1/\epsilon))$ operations. Since the SCA procedure requires I_1 iterations, the total complexity of Phase 1 is given by $\mathcal{O}(I_1(NK)^{3.5} \log(1/\epsilon))$.

Algorithm 1 Proposed Algorithm

```

1: Set  $r = 0$  and initialize  $\alpha, \beta, \delta, s, p, c, \rho, \kappa, v, v_{\max}$ , and  $\gamma > 1$ 
2: Calculate  $\eta^r = T_D + \omega\eta_D$  based on these initial values
3: repeat
4:    $r \leftarrow r + 1$ 
5:    $\eta^{\text{old}} \leftarrow \eta^{r-1}$ 
6:   Find  $\{\alpha^r, \beta^r, \delta^r, c^r, \rho^r, \kappa^r\}$  by solving (P1-2) for given  $\{\alpha^{r-1}, \beta^{r-1}, \delta^{r-1}, c^{r-1}, \rho^{r-1}, \kappa^{r-1}\}$ 
7:   Update  $v^r = \min\{\gamma v^{r-1}, v_{\max}\}$ 
8:   Calculate  $\eta^r = T_D + \omega\eta_D + v^r \mathcal{P}(\rho^r, \kappa^r)$ 
9: until  $|\eta^r - \eta^{\text{old}}| \leq \epsilon$ 
10: Fix  $\{\alpha, \beta\}$  and the trajectory up to the slot  $\eta_D$ , and set  $\delta[n] = (T - T_D)/(N - \eta_D)$  for all  $n > \eta_D$ 
11: Calculate  $\eta^r = \min_{l \in \mathcal{L}} R_l$ 
12: repeat
13:    $r \leftarrow r + 1$ 
14:    $\eta^{\text{old}} \leftarrow \eta^{r-1}$ 
15:   Find  $c^r$  by solving (SP2-3') for given  $\{s^{r-1}, p^{r-1}, c^{r-1}\}$ 
16:   Find  $s^r$  by solving (SP2-1) for given  $\{s^{r-1}, p^{r-1}, c^r\}$ 
17:   Find  $p^r$  by solving (SP2-2) for given  $\{s^r, p^{r-1}, c^r\}$ 
18:   Calculate  $\eta^r = \min_{l \in \mathcal{L}} R_l$ 
19: until  $|\eta^r - \eta^{\text{old}}| \leq \epsilon$ 
  
```

In Phase 2, the communication optimization is further decomposed into scheduling, transmit-power, and trajectory subproblems. The scheduling variables $s_l[n]$ scale with NL , while the transmit-power and trajectory variables mainly scale with N . Therefore, the scheduling variables dominate the complexity of the Phase-2 loop, yielding an effective problem size of order NL . Thus, each SCA iteration in Phase 2 has a worst-case complexity of $\mathcal{O}((NL)^{3.5} \log(1/\epsilon))$. With I_2 iterations, the total complexity of Phase 2 becomes $\mathcal{O}(I_2(NL)^{3.5} \log(1/\epsilon))$. Combining the two phases, the overall worst-case complexity of Algorithm 1 is

$$\mathcal{O}\left(I_1(NK)^{3.5} \log(1/\epsilon) + I_2(NL)^{3.5} \log(1/\epsilon)\right). \quad (42)$$

This polynomial-order complexity indicates that the proposed algorithm is computationally tractable for planning-stage UAV mission optimization. Since the method relies on iterative convex optimization, it is not intended for online slot-by-slot control. Rather, it is suitable for offline mission planning, where the UAV trajectory and resource-allocation policy are computed before the mission under known pickup/delivery zones, GN locations, and mission duration.

Remark 1 (Practical applicability). *The practical application of the proposed framework is subject to several operating boundaries. The framework is most suitable for planning-stage UAV missions in which the delivery task is feasible under the given flight period, UAV speed, and payload capacity. If these logistics requirements become too stringent, such as an excessively short mission time, slow UAV speed, or insufficient payload capacity, the delivery phase may no longer provide a feasible basis for communication optimization. In addition, the current communication model assumes LoS-dominant distance-based channels; therefore, highly dynamic blockage, severe non-LoS propagation, or imperfect CSI may require robust or stochastic channel modeling and online replanning. Finally, the time discretization should be sufficiently fine to represent UAV movement, descent/ascent operations, and scheduling decisions. These boundary conditions should be considered when applying the proposed framework to practical UAV delivery and communication missions.*

4. Performance Evaluation and Discussion

For the simulation setup, we consider a square mission area of $500\text{ m} \times 500\text{ m}$, where the pickup zones, delivery zones, and GNs are randomly and uniformly distributed. This setting represents a local urban-scale UAV mission in which the UAV performs short-range parcel delivery while providing downlink communication service to spatially distributed GNs. Unless otherwise stated, we set $K = 3$ items and $L = 4$ GNs to clearly illustrate the coupling between item-handling operations and communication scheduling without overcrowding the trajectory figures. The total mission period is set to $T = 80\text{ s}$ and divided into $N = 100$ adjustable time slots, which provides sufficient temporal resolution for modeling UAV movement, item pickup/drop-off, and communication scheduling. The default values of the delivery-index weighting coefficient, UAV flight speed, altitude, maximum payload capacity, pickup/delivery-zone tolerance, communication power budgets, channel parameters, penalty parameters, and convergence threshold are selected based on commonly used settings in previous UAV communication and logistics studies [6,8,12–14,18] and are summarized in Table 1. The performance of the proposed scheme is compared with the following four baseline schemes.

Table 1. Parameter setup.

Description	Value
Number of GNs	$L = 4$
Number of items	$K = 3$
Flight period	$T = 80\text{ s}$
Number of time slots	$N = 100$
Delivery-index weighting coefficient	$\omega = 1\text{ s/slot}$
Maximum flight speed	$V_{\max} = 30\text{ m/s}$
Altitude	$H = 20\text{ m}$
Maximum payload capacity	$W_{\max} = 30\text{ kg}$
Tolerance for pickup and delivery zones	$R_k = \hat{R}_k = 1\text{ m}, \forall k$
Average channel power gain	$\mu_0 = -30\text{ dB}$
Noise power	$\sigma^2 = -100\text{ dBm}$
Average transmit power	$P_{\text{avg}} = 30\text{ dBm}$
Peak transmit power	$P_{\text{peak}} = 4 \times P_{\text{avg}}$
Penalty parameters	$\{\nu^0, \nu_{\max}, \gamma\} = \{100, 10^5, 1.2\}$
Convergence threshold	$\epsilon = 10^{-3}$

1. *Proposed scheme*: The UAV strategy including α , β , δ , s , p , and c are optimized by Algorithm 1.
2. *Fixed scheduling scheme*: The total mission time T is evenly divided into L segments, and each GN is exclusively scheduled in its assigned segment according to the GN index order, while the other variables are optimized by Algorithm 1.
3. *Fixed power scheme*: The UAV allocates its transmit power using a simple distance-aware rule, assigning slightly higher power to time slots with shorter UAV–GN distances while satisfying both peak and average power constraints, whereas the other variables are optimized by Algorithm 1.
4. *Fixed trajectory scheme*: The UAV follows the delivery-mission-optimized path at a constant speed throughout the mission duration T , while the other variables are optimized by Algorithm 1.
5. *Fixed delivery scheme*: The UAV first collects all items from their pickup zones and then performs all deliveries afterward, without interleaving pickup and delivery operations, while the other variables are optimized by Algorithm 1.

We adopt ablation-type baseline schemes derived from the proposed framework, where one key component is fixed while the remaining variables are optimized. These baselines enable a fair and controlled evaluation of the individual contributions of adaptive GN scheduling, transmit-power control, residual trajectory optimization, and flexible pickup/drop-off ordering. In the reported simulations, all tested cases were successfully solved without numerical failure under the parameter settings in Table 1.

Figure 2 illustrates the trajectory and resource allocation of the proposed scheme. Specifically, Figure 2a shows the optimized UAV trajectory for $T = 80$ s, where blue squares indicate the origin and destination, empty circles with item weights denote pickup zones, empty diamonds mean delivery zones, and filled circles represent GNs. The trajectory is segmented with different colors to show which GN is served at each time slot. As shown in this result, when the available flight time is sufficiently long, the UAV is not only able to visit all pickup and delivery zones but also approaches most of the GNs to provide high-quality communication services. The UAV first executes Phase 1 optimization to complete all pickup and delivery tasks as early as possible and then performs Phase 2 optimization to refine GN scheduling and transmit power allocation over the entire mission horizon, while further optimizing the remaining trajectory segment for communication enhancement. In Figure 2b (upper subfigure), both the pickup and drop-off indicators correctly switch to one only during the time slot assigned for that task, demonstrating the binary feasibility of the assignment variables. The altitude trace also confirms that the UAV descends into each pickup and delivery zone within approximately 1 m accuracy, validating the effectiveness of the spatial and altitude constraints during item-handling operations. In Figure 2b (lower subfigure), the evolution of the time-slot duration shows distinct behaviors across the two phases. During Phase 1, the slot lengths are optimized to minimize the delivery completion time by dynamically shortening or lengthening slots depending on travel and descent requirements. Once all items are delivered, the UAV enters Phase 2, where the remaining mission time is evenly distributed across the residual slots, resulting in a constant slot duration throughout the communication interval. These results show how the proposed framework separates the logistics and communication roles over the mission timeline. During the logistics phase, altitude changes and variable slot lengths are mainly determined by pickup/drop-off operations and service-zone constraints. After the delivery tasks are completed, the residual mission interval is used for communication enhancement, where the UAV can exploit the remaining time and mobility resources more flexibly. Figure 2c further shows the resource-allocation patterns optimized during Phase 2. In the upper subfigure, the UAV schedules communication to the geographically closest GN along the trajectory at each time slot, and the binary scheduling indicators exhibit valid 0/1 activation without fractional values. In the lower subfigure, the transmit power is dynamically adjusted in accordance with the varying UAV–GN channel quality, thereby improving communication efficiency. The scheduling and power-control results further indicate that the UAV compensates for unfavorable channel conditions by allocating communication opportunities and transmit power according to the relative UAV–GN geometry. This explains why the proposed method can improve the minimum average SE even when some GNs are not located close to the delivery path.

Figure 2d shows the optimized UAV trajectory for $T = 60$ s. In this case, the shorter flight period leaves only a limited amount of time after completing the pickup and drop-off operations, so the resulting trajectory cannot pass near most of the GNs. As a result, GN 4, which happens to lie close to the flight path, is allocated relatively few time slots, whereas the remaining GNs that cannot be directly visited receive more scheduling time to compensate for their weaker channel conditions and thereby enhance overall communication

efficiency. Apart from this behavior, the general resource allocation patterns in Figure 2e,f remain consistent with the case of $T = 80$ s.

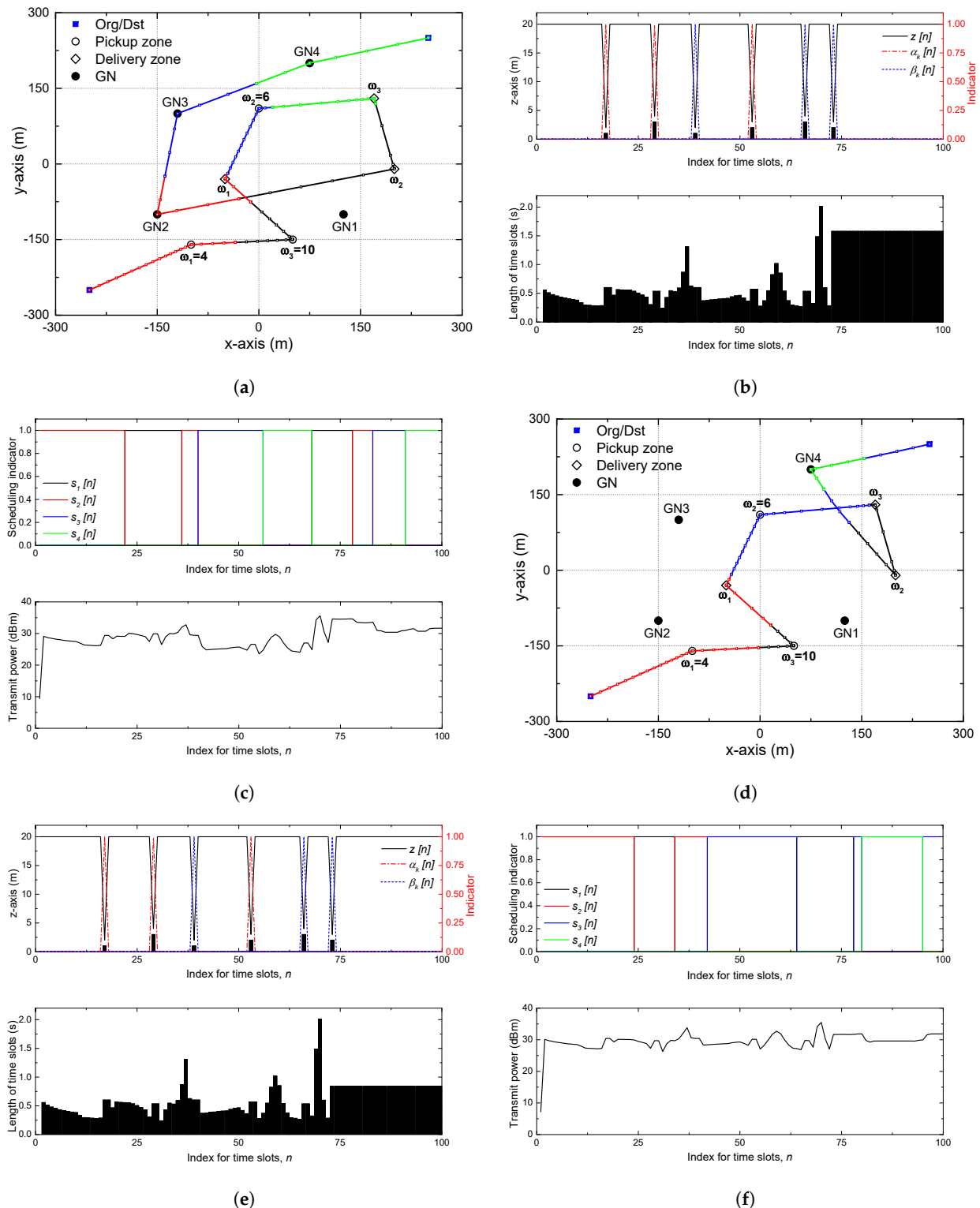


Figure 2. Trajectory and resource allocation of proposed scheme. (a) Horizontal trajectory when $T = 80$ s. (b) Vertical trajectory and length of time slots when $T = 80$ s. (c) Scheduling and transmit power when $T = 80$ s. (d) Horizontal trajectory when $T = 60$ s. (e) Vertical trajectory and length of time slots when $T = 60$ s. (f) Scheduling and transmit power when $T = 60$ s.

Figure 3 provides the performance comparison of different schemes under various system parameters. In particular, Figure 3a,b jointly present the average SE and delivery completion time for different values of the maximum flight speed ($V_{\max}$). Since $V_{\max}$ determines the UAV's maximum flight speed, a larger $V_{\max}$ enables the UAV to traverse the pickup and delivery locations more quickly, which reduces the delivery completion time. Finishing the delivery mission earlier leaves more time for communication service, thereby improving the achieved SE. While most schemes exhibit noticeable SE improvement as $V_{\max}$ increases, the fixed trajectory scheme shows nearly unchanged performance. This is because the UAV maintains a fixed flight path focused on the delivery mission at a constant speed during the given mission duration T . As a result, varying $V_{\max}$ does not significantly alter the effective trajectory in terms of the communication optimization, and the achievable SE remains almost the same. The performance ordering of the baselines is consistent with their degrees of freedom. For example, the fixed power scheme provides the highest performance among the baselines because only the transmit power is fixed while delivery order, trajectory, and scheduling remain optimizable. The fixed delivery also performs relatively well since, despite a fixed pickup/drop-off sequence, the UAV can still optimize its trajectory and communication scheduling. In contrast, the fixed trajectory severely limits the potential of trajectory–communication coupling, resulting in lower performance, and the fixed scheduling yields the worst performance due to the mismatch between its predetermined GN service order and the delivery-driven UAV trajectory.

Figure 3c,d examine the impact of the flight period (T) and average transmit power (P_{avg}) on the average SE. Since neither parameter affects the delivery completion time in Phase 1, only SE results are reported without plotting the delivery time. As T increases, most schemes achieve higher SE because more mission time becomes available for communication after the delivery operations, enlarging the degrees of freedom in GN scheduling, power allocation, and residual flight trajectory. The fixed trajectory scheme, however, shows almost unchanged performance because its delivery-oriented path is fixed and cannot be reshaped to exploit the additional time for communication enhancement. An interesting trend is that the fixed power scheme eventually outperforms the fixed delivery scheme as T grows. At small values of T , the fixed power scheme cannot fully capitalize on its flexible trajectory and scheduling because very little time is left after finishing the delivery task. As T becomes larger, the communication phase dominates the mission duration, and the fixed power scheme is able to leverage its greater adaptability to improve SE, eventually outperforming the fixed delivery scheme. Furthermore, increasing P_{avg} improves the SE of all schemes because a larger average power budget more effectively compensates for unfavorable UAV–GN channel conditions, especially when the UAV is distant from the scheduled GN. The proposed scheme consistently outperforms all baseline methods across all parameter settings. This is because the proposed method not only completes the delivery mission early but also effectively exploits the residual mission interval through joint coordination of GN scheduling, transmit power, residual trajectory, and delivery ordering. In contrast, each baseline fixes at least one of these components, which limits its ability to convert the remaining mission time into communication performance gains.

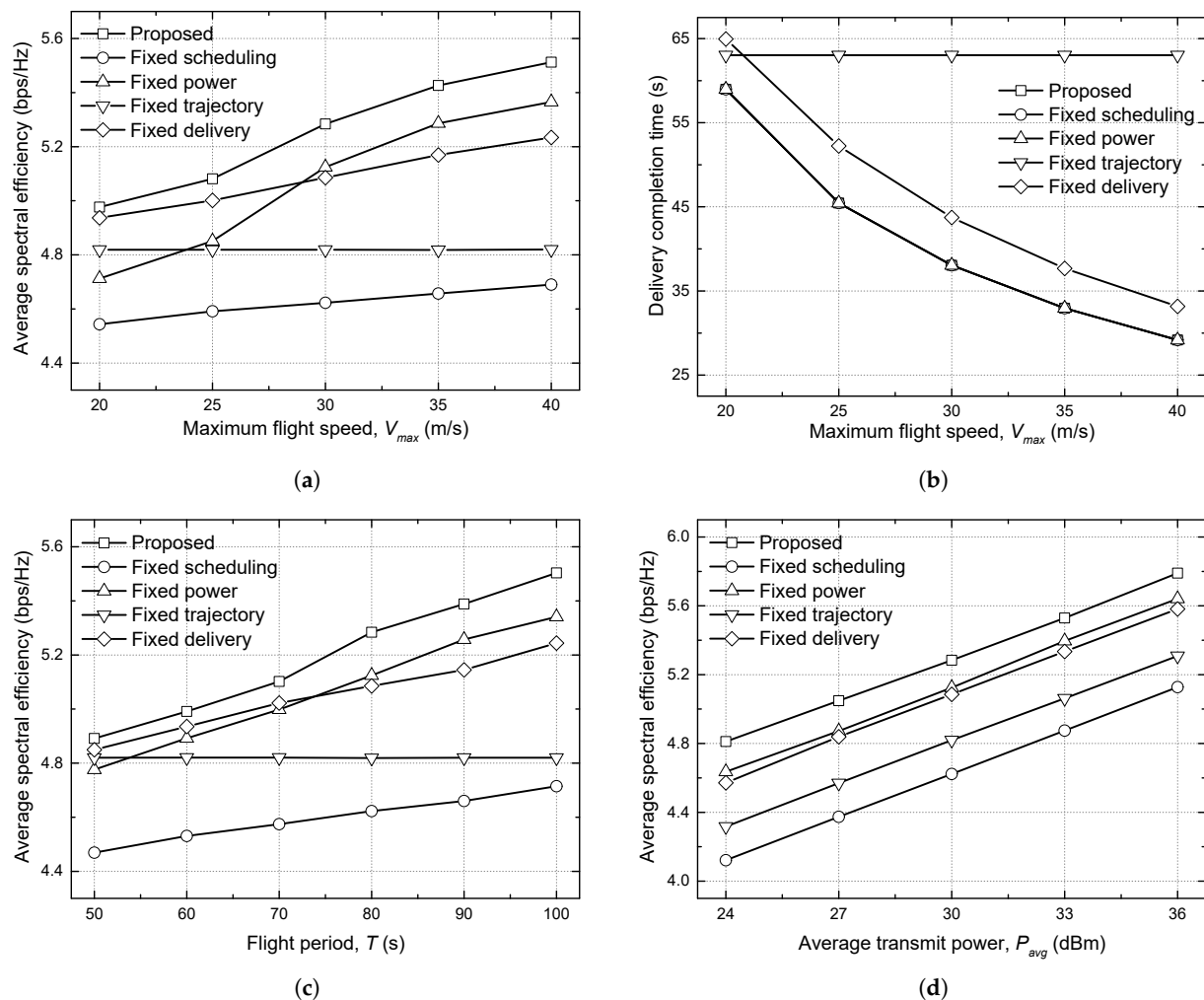


Figure 3. Performance comparisons against various parameters. (a) Average spectral efficiency vs. V_{max} . (b) Delivery completion time vs. V_{max} . (c) Average spectral efficiency vs. T . (d) Average spectral efficiency vs. P_{avg} .

5. Conclusions

This paper investigated a UAV communication system integrated with parcel pickup-and-delivery missions, where logistics operations and downlink communication are coupled through UAV trajectory, time allocation, and resource management. To prevent the strict pickup-and-delivery constraints from dominating the unified optimization, we proposed a two-phase optimization framework that separates the logistics-dominated delivery stage from the communication-oriented residual service stage. In Phase 1, the UAV obtains a feasible and time-efficient pickup-and-delivery plan under spatial, payload, and binary item-handling constraints. In Phase 2, communication performance is enhanced by optimizing GN scheduling and transmit power over the entire mission horizon, together with post-delivery trajectory refinement. Simulation results showed that the proposed framework consistently improves the minimum average SE compared with baseline schemes by effectively exploiting the residual mission time after delivery completion. The proposed framework also has several limitations and trade-offs. The two-phase decomposition improves tractability and avoids the strong feasibility burden of the original MINLP, but it does not guarantee global optimality for the unified problem. In addition, the current formulation assumes LoS-dominant distance-based channels and is more suitable for planning-stage offline optimization with known pickup/delivery zones, GN locations, and mission horizon, rather than real-time control in highly dynamic or

uncertain environments. In future work, the proposed framework can be extended from planning-stage optimization to more dynamic and uncertain UAV networking scenarios by incorporating robust channel modeling, online replanning, and learning-assisted adaptation. Such extensions would allow the UAV to respond more effectively to time-varying delivery requests, traffic demand, and channel conditions while preserving the explicit logistics and communication constraints.

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