

Resilience-Aware Completion Time Minimization in Cooperative Multi-UAV Data Processing System

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Abstract—Recent advances in mobile edge computing (MEC) have transformed unmanned aerial vehicles (UAVs) into intelligent platforms capable of distributed sensing, computing, and communication. However, coordinating multiple UAVs presents significant challenges in task assignment, path planning, and resource allocation. To address these issues, we propose a *joint task assignment and resource allocation optimization (TARO)* approach for efficient target point (TP) visit in multi-UAV MEC systems. Specifically, considering resilience in this work, each TP may require multiple visits, while each UAV is restricted to visiting any given TP only once, leading to non-overlapping visit requirements. We formulate an optimization model as a mixed-integer nonlinear programming (MINLP) to minimize the maximum task completion time among all UAVs. To solve the problem efficiently, we adopt a Benders-inspired decomposition framework with infeasibility elimination, which separates the original problem into a routing master problem and two continuous subproblems. In addition, efficient solution approaches (e.g., closed-form solution) are developed to solve them respectively. Simulation results show that TARO significantly reduces latency and enforces temporally separated repeated visits to the same TP under various mission configurations and bandwidth constraints, thereby improving resilient mission performance.

Index Terms—Unmanned aerial vehicle, mobile edge computing, task assignment, path planning, bandwidth allocation.

I. INTRODUCTION

UNMANNED aerial vehicles (UAVs) are profoundly reshaping a wide range of critical sectors such as agriculture, logistics, environmental surveillance, and disaster management, by facilitating high-efficiency data acquisition

and continuous monitoring over extensive and complex geographical areas [2], [3]. In contrast to conventional ground infrastructure [4], UAV systems provide exceptional operational flexibility and extensive spatial coverage, enabling swift deployment, enhanced maneuverability, and robust adaptability to dynamic and intricate environmental conditions [5], [6]. Although UAVs demonstrate significant advantages, their performance is fundamentally limited by constrained onboard computing power and limited energy capacity, which hinders their ability to independently perform complex and demanding missions [7], [8].

To address these inherent limitations, it is common practice to offload computational workloads to remote servers, thereby reducing the processing burden placed on the UAV platforms [9], [10]. However, transmitting tasks to geographically distant cloud servers may lead to significant communication delays, which can severely impact the performance of applications that are sensitive to latency [11]. As a promising alternative, mobile edge computing (MEC) enables UAVs to offload tasks to nearby edge servers, significantly reducing transmission delays and enhancing computational efficiency [12], [13]. For analytical tractability, this work adopts a commonly used quasi-static line-of-sight (LoS) communication model, which is widely adopted in UAV-assisted MEC literature [14], [15]. We note that the resilience considered in this work mainly refers to mission-level robustness achieved through repeated TP visits, cooperative scheduling, and joint resource optimization. More realistic air-to-ground channel effects, such as NLoS propagation, blockage, and small-scale fading, are not explicitly modeled in the current formulation and will be incorporated in future work.

Recent research on UAV systems integrated with MEC has emphasized their potential in alleviating the computational and energy constraints commonly faced by UAV platforms [16]. However, most existing studies concentrate on scenarios involving a single UAV cooperating with a single edge server, which often fails to provide the scalability required for practical and large-scale deployments [17]. In practical scenarios, multiple UAVs are often required to cooperate in a coordinated manner to ensure wide area coverage and manage complex mission demands, since a single UAV with mobile edge computing configuration is typically insufficient to support operations at large scale [18], [19]. Consequently, improving the efficiency and effectiveness of collaborative frameworks involving multiple UAVs and mobile edge computing has emerged as a vital area of research [20]–[22].

Our work specifically addresses the unique challenges posed

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The work of J. Tang was supported in part by the National Natural Science Foundation of China under Grant 62571199, in part by the National Key R&D Program of China under Grant 2024YFE0200500, in part by the Guangdong Basic and Applied Basic Research Foundation under Grant 2024A1515012615, and in part by the Key Laboratory of Cognitive Radio and Information Processing, Ministry of Education under Grant CRKL240201. The work of Z. Liu was supported in part by the Royal Society under Grants IEC\NSFC\233292 and IES\R1\241212. Part of this paper [1] has been presented at the 2025 IEEE 102nd Vehicular Technology Conference: VTC2025-Fall, Chengdu, China, October, 2025.

by multi-UAV MEC systems, focusing on improving task allocation, path planning, and coordination among UAVs. In contrast to approaches that treat UAVs as MEC servers serving ground users, which require them to function as edge nodes with onboard processing capabilities and consequently face complex resource management issues [23], [24], our method focuses on optimizing the cooperation between multiple UAVs and a centralized MEC. This architecture, which relies on a centralized mobile edge computing server, avoids the energy consumption and resource management challenges inherent in UAV based edge processing, thereby offering a more suitable solution for scenarios that require high task processing rates and low communication latency [25], [26].

In addition, resilience has emerged as a vital requirement for multi-UAV MEC systems, since real-world deployments often suffer from uncertain sensing environments, time-varying wireless links, and unexpected UAV failures [27], [28]. In practical sensing and monitoring missions, a single visit to a TP may be insufficient due to sensing uncertainty, packet loss, temporary communication interruption, or partial task execution failure. Therefore, certain critical TPs may require redundant visits by multiple UAVs to improve data reliability and task completion robustness. To address these challenges, cooperative scheduling and redundant task allocation among UAVs are introduced to enhance robustness and provide temporal-spatial diversity [29]. Such resilient coordination improves mission robustness by enabling redundant and temporally separated visits to critical TPs, thereby reducing the risk of incomplete task processing under sensing uncertainty or temporary communication interruption.

In this paper, we propose a novel framework, named the *joint task assignment and resource allocation optimization (TARO)*, that integrates multi-UAV collaboration with MEC to optimize data processing at TPs. Compared with our previous conference work [1], which focused on basic UAV-TP association, offloading decision, and bandwidth allocation under the assumption that each TP is visited once, the journal version significantly extends the framework in several aspects. Specifically, we introduce resilience-aware task modeling by allowing multiple visits to selected TPs, incorporate temporal conflict-avoidance scheduling for repeated TP visits, and provide a more comprehensive joint optimization framework that simultaneously considers routing, task offloading, and bandwidth allocation. The proposed framework is designed to minimize the task completion time across multi-UAVs by ensuring mission resilience, which allows multiple visits to some TPs. And then enhancing multi-UAV collaborations via balancing task allocations, dynamically adjusting UAV to TP associations, optimizing offloading decisions, and efficiently distributing communication bandwidth among UAVs.

The main contributions of this paper are as follows:

- We introduce a multi-UAV cooperative MEC system with the TARO approach, jointly optimizing UAV-TP association, time scheduling, task offloading decisions and bandwidth allocation to minimize the maximum task completion time across all UAVs. This extends our prior conference work by additionally considering task prioritization, repeated TP visits to enhance mission resilience,

and temporal conflict-avoidance scheduling for repeated TP visits.

- To tackle the mixed-integer nonlinear structure of the optimization problem, we adopt a Benders-inspired decomposition framework with infeasibility elimination, which partitions the original problem into one master problem and two interrelated subproblems. Through the branch-and-bound method for UAV-TP association and time scheduling, a closed-form solution for the task offloading ratio, and a binary search method for bandwidth allocation, we develop the TARO approach to jointly optimize UAV-TP assignment, temporal conflict-avoidance scheduling for repeated TP visits, offloading ratio, and bandwidth allocation.
- Through extensive simulation studies, we demonstrate that the proposed TARO approach significantly outperforms existing benchmark schemes in minimizing overall task completion time while ensuring mission resilience.

The remainder of this paper is organized as follows. Section II reviews the related work. Section III describes the system model and formulates the joint task assignment and resource allocation problem in multi-UAV MEC systems. Section IV details the proposed TARO algorithm, including its decomposition into a master problem and two subproblems, along with the solution methods. Section V presents simulation results under various mission scenarios, evaluating the performance of the proposed approach against benchmark algorithms. Finally, Section VI concludes the paper and outlines potential directions for future research.

II. RELATED WORKS

This section reviews representative studies related to the proposed resilience-aware cooperative multi-UAV MEC framework. Specifically, we discuss UAV-assisted mobile edge computing, multi-UAV collaboration, task assignment and routing, computation offloading, and resource allocation. We then summarize the differences between existing works and the proposed TARO framework through a comparison table.

A. UAV-Assisted Mobile Edge Computing

The convergence of UAV and MEC has gained considerable attention as a promising paradigm that enhances the processing capabilities of UAVs while alleviating their inherent limitations in energy capacity and computational power [30]. Within this research direction, trajectory optimization plays a key role in improving communication efficiency and reducing service latency [31]. For example, [32]–[34] jointly optimize UAV trajectories and computation offloading to enhance sensing efficiency and reduce energy consumption. Several studies [35], [36] investigate trajectory optimization in UAV-assisted MEC systems by jointly designing task scheduling, offloading, and flight paths to minimize the weighted sum of energy consumption and task delay. [37] optimizes UAV trajectories together with computation offloading and resource allocation to maximize the number of served users under latency and energy constraints. Other recent studies further consider robust multi-UAV-assisted MEC by jointly optimizing computation

offloading and UAV trajectories [38]. However, most existing works assume fixed UAV start and end locations and focus on continuous trajectory optimization. In contrast, our work considers a more practical setting where multiple UAVs collaboratively determine routes by dynamically associating with spatially distributed TPs.

B. Multi-UAV Collaboration, Task Allocation and Routing

To enable efficient multi-UAV cooperation, recent studies focus on joint task allocation and resource coordination strategies that consider UAV interactions and system-level objectives [39], [40]. [41] studies multi-UAV path planning for MEC task offloading and proposes a multi-strategy improved particle swarm optimization algorithm to minimize total task delay. [42] studies dynamic trajectory planning for multiple UAVs in MEC networks by formulating a multi-objective optimization problem considering energy, delay, and link quality, and solves it using a non-dominated sorting genetic algorithm. [43] proposes an attention-based reinforcement learning framework for cooperative trajectory and control optimization in multi-UAV MEC systems, enabling adaptive path planning and resource allocation. [44] investigates joint UAV deployment and user association optimization in MEC networks to minimize delay and UAV energy consumption, with UAV trajectories adapting to user mobility. [45] optimizes UAV trajectories and power control in a joint radar-communication system to enhance sensing accuracy and transmission reliability.

In addition to trajectory planning and resource coordination, task allocation and routing are essential for cooperative multi-UAV missions, since the assignment of target points to UAVs directly affects workload balancing, route feasibility, and mission completion time. Recent studies have therefore formulated multi-UAV task allocation and path planning as combinatorial optimization or learning-based problems. For example, [46] investigates reinforcement-learning-assisted multi-UAV task allocation and path planning for IIoT, while [47] studies multi-UAV task allocation problems with complex constraints using a dual-neighborhood search-based dual-population coevolutionary algorithm. [48] studies cooperative task scheduling for multiple UAVs in dynamic environments and formulates a throughput maximization problem. In MEC-oriented UAV networks, [49] further considers UAV trajectory generation under uncertain obstacle avoidance, highlighting the importance of practical route-planning constraints in UAV-assisted MEC systems.

While these studies provide useful insights into multi-UAV coordination, task allocation, and routing, most of them follow conventional one-visit task models and do not jointly consider repeated TP visits, temporal conflict-avoidance scheduling, task offloading, and communication resource allocation. In contrast, the proposed TARO framework addresses these coupled decisions in a resilience-aware cooperative multi-UAV MEC system.

C. Computation Offloading and Resource Allocation

To address the intertwined challenges of computation offloading and communication resource allocation in UAV-

assisted MEC systems, recent works have introduced various joint optimization frameworks [50]. The work in [51] investigates resource allocation in UAV-assisted NOMA systems by jointly optimizing power allocation and user pairing to maximize throughput, where a matching theory-based algorithm is developed. The study in [52] jointly optimizes UAV trajectory, task offloading, and communication resources to minimize weighted delay and energy consumption through a three-layer alternating optimization framework. Similarly, [53] studies energy-efficient resource allocation in secure D2D-enabled UAV communications by formulating a non-convex optimization problem, which is solved using alternating optimization and successive convex approximation. Learning-based resource allocation has also been explored; for example, [54] proposes a deep Q-learning-based framework for adaptive power and bandwidth allocation in UAV networks. The work in [55] designs a fairness-aware joint task scheduling and resource allocation scheme using Lyapunov optimization to balance delay and user fairness in UAV-assisted MEC networks. In addition, [56] jointly optimizes UAV placement and resource allocation using a convex approximation-based iterative algorithm to maximize the system utility in multi-user MEC networks.

Recent studies have further investigated the joint design of task offloading, resource allocation, and UAV trajectory optimization in multi-UAV MEC systems. For example, [57] studies cooperative task offloading and resource allocation for multi-UAV systems in 5G Advanced and beyond. The work in [58] proposes an optimization-embedding multi-agent deep reinforcement learning framework for joint UAV trajectory and task offloading. The study in [59] jointly optimizes task offloading, resource allocation, and trajectory design for multi-UAV cooperative edge computing with task priority. In addition, [60] investigates task offloading and resource allocation in UAV-assisted MEC from a privacy-preserving auction perspective.

Although these works provide effective solutions for offloading and resource management, most of them follow conventional task-service models and do not jointly consider repeated TP visits, temporal conflict-avoidance scheduling, UAV routing, task offloading, and bandwidth allocation. In contrast, the proposed TARO framework addresses these coupled decisions in a resilience-aware cooperative multi-UAV MEC system.

D. Summary and Comparison with Existing Works

The above studies have made important contributions to UAV-assisted MEC, multi-UAV collaboration, task allocation and routing, computation offloading, and resource allocation. However, most existing works focus on only part of the overall problem, such as trajectory design, task offloading, routing, or communication resource management. The joint consideration of resilience-aware repeated TP visits, temporal conflict-avoidance scheduling, UAV routing, task offloading, and bandwidth allocation remains insufficiently explored. To further clarify the positioning of this work, Table I compares the proposed TARO framework with representative existing studies.

TABLE I
COMPARISON OF THE PROPOSED TARO FRAMEWORK WITH REPRESENTATIVE EXISTING WORKS

Works	Main Focus	Multi-UAV	Routing / Task Allocation	Offloading / Resource Allocation	Resilience Modeling	Repeated Visits and Temporal Separation
UAV-assisted MEC studies [30]–[38]	Trajectory optimization, edge computing, and computation offloading	Partial	Limited	Yes	No	No
Multi-UAV task allocation and routing studies [39]–[49]	Multi-UAV cooperation, task allocation, path planning, and routing optimization	Yes	Yes	Partial	Limited	No
Offloading and resource allocation studies [51]–[60]	Computation offloading, bandwidth/power allocation, and joint resource optimization	Partial	Limited	Yes	Limited	No
Proposed TARO	Resilience-aware completion time minimization in cooperative multi-UAV MEC	Yes	Yes	Yes	Yes	Yes

Note: Existing UAV-assisted MEC studies mainly focus on one-time task service, trajectory optimization, task allocation, or resource management, and thus do not explicitly model repeated visits to the same physical TP. In contrast, TARO introduces non-concurrent repeated visits and temporal separation to capture heterogeneous mission resilience requirements.

III. SYSTEM MODEL AND PROBLEM FORMULATION

We investigate a cooperative multi-UAV system, as illustrated in Fig. 1, which consists of multiple UAVs and TPs. The system is designed to enable collaborative processing of computational tasks at the network edge through inter-UAV cooperation. For simplicity, it is assumed that each TP is preloaded with the data required for processing prior to the arrival of the UAVs. Let $\mathcal{U} = \{U_1, U_2, \dots, U_K\}$ represent the set of UAVs, where K denotes the total number of UAVs in the system. Similarly, define $\mathcal{V} = \{V_1, V_2, \dots, V_N\}$ as the set of TPs, with N representing the total number of TPs. Each UAV U_k initiates its mission from a designated starting location denoted by $\mathbf{Q}_k^{\text{start}}$, ascends to and maintains a fixed altitude H , sequentially visits its assigned TPs to execute the required computational tasks, and subsequently returns to its initial location to complete the operational cycle. The position of the base station (BS) is denoted by $\mathbf{Q}_{\text{BS}} \in \mathbb{R}^{2 \times 1}$, while the location of each TP V_i is specified by a coordinate vector $\mathbf{Q}_i \in \mathbb{R}^{2 \times 1}$. The three-dimensional distance d_i between TP V_i and the BS is computed as

$$d_i = \sqrt{H^2 + \|\mathbf{Q}_i - \mathbf{Q}_{\text{BS}}\|_2^2}, \quad V_i \in \mathcal{V}, \quad (1)$$

where H denotes the fixed flight altitude of the UAVs, and $\|\cdot\|_2$ represents the Euclidean norm.

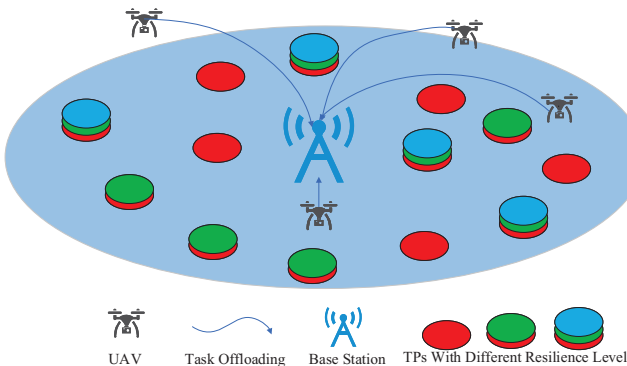


Fig. 1. Multi-UAV resilient data processing system.

A. Mission Resilience and UAV-TP Assignment Model

Building upon the aforementioned system model, we now consider the heterogeneity of computational task complexity across different TPs. In practical scenarios, the data associated with certain TPs may exhibit high levels of noise, ambiguity, or structural deception, rendering a single UAV visit insufficient for accurate and complete task execution. Consequently, multiple visits may be required to ensure reliable and resilient processing outcomes.

To capture this variability, we introduce a mission resilience model that quantifies the visit demand associated with each TP. Specifically, let O_i denote the resilience level of TP V_i .

- A value of $O_i = 1$ indicates that the task in this TP is relatively simple and can be fully processed by a single UAV visit.
- In contrast, a higher value $O_i > 1$ reflects an increased level of task complexity, necessitating *at least* O_i non-concurrent visits to the TP by O_i different UAVs, in order to meet the resilience requirements.

The resilience level O_i specifies the required number of independent and non-concurrent visits for TP V_i . It represents a mission-level redundancy requirement rather than a physical failure probability. When sensing uncertainty, packet loss, temporary communication interruption, or UAV-side execution failure occurs, a single visit may lead to incomplete or unreliable task processing. By requiring O_i visits from different UAVs at different times, the system provides both spatial redundancy across UAVs and temporal redundancy across visits. For example, when $O_i = 2$, TP V_i must be visited by two different UAVs in a non-concurrent manner, such that one visit can still support task completion if the other is affected by sensing or communication failures.

In order to efficiently handle the multiple visit requirements of TPs with different priorities, we adopt the duplicate-node modelling approach [61]. Specifically, for each TP V_i and its resilience level O_i , we generate O_i duplicate TPs, denoted as $\hat{\mathcal{V}} = \{V_{i,1}, V_{i,2}, \dots, V_{i,O_i}\}$. Each duplicate TP represents a separate visit requirement to the original TP, ensuring that each visit is handled separately.

To characterize the travel trajectories of the UAVs, we introduce a binary decision variable $\alpha_{i,(j,q)}^k$ defined as

$$\alpha_{i,(j,q)}^k = \begin{cases} 1, & \text{if UAV } U_k \text{ travels from } V_i \text{ to } V_{j,q}, \\ 0, & \text{otherwise,} \end{cases} \quad (2)$$

where q denotes the index of the q -th visit to TP V_j , and $\alpha_{i,(j,q)}^k$ indicates whether UAV U_k flies directly from V_i to V_j during its q -th visit. Each TP must be visited exactly once by one UAV during a specific visit, which is ensured by the following constraint

$$\sum_{k=1}^K \sum_{i=0}^N \alpha_{i,(j,q)}^k = 1, \quad \forall V_{j,q} \in \tilde{\mathcal{V}}. \quad (3)$$

To preclude any single UAV U_k from servicing more than one duplicate of the same TP, we impose the following constraint on its assignment variables

$$\sum_{i=0}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k \leq 1, \quad \forall V_j \in \mathcal{V}, U_k \in \mathcal{U}. \quad (4)$$

When executing missions, UAVs are typically subject to constraints that reflect their physical and operational limitations. Although energy-based constraints are widely used to characterize UAV endurance, accurate energy modeling usually depends on multiple dynamic factors, such as flight speed, wind conditions, hovering time, and payload [62], [63]. Therefore, in the present work, we adopt a simplified visit-budget constraint as a coarse endurance and workload control mechanism for each UAV, which allows us to focus on resilience-aware completion-time minimization while maintaining analytical tractability. We note that this constraint is not intended to replace a full physical energy model. Incorporating explicit flight energy and computation energy consumption into the resilience-aware optimization framework is an important direction for future work. Specifically, the total number of TPs visited by UAV U_k is constrained by a predefined upper bound L_k , formulated as:

$$\sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k \leq L_k, \quad U_k \in \mathcal{U}. \quad (5)$$

Each UAV is required to both initiate and terminate its mission at its designated starting location $\mathbf{Q}_{\text{start}}^k$. To model this behavior, we define $\alpha_{0,(j,q)}^k = 1$ if UAV U_k travels from its starting location to TP $V_{j,q}$, and $\alpha_{(j,q),0}^k = 1$ if UAV U_k returns from TP copy $V_{j,q}$ to the starting location. This requirement is captured by the following constraints

$$\sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{0,(j,q)}^k = 1, \quad \sum_{i=1}^N \alpha_{i,(0,1)}^k = 1, \quad U_k \in \mathcal{U}. \quad (6)$$

To ensure route feasibility and connectivity, additional continuity constraints are introduced. In particular, for each duplicated TP and UAV, flow conservation is enforced to prevent disconnected subtours. Accordingly, for each duplicated TP $V_{j,q}$ and UAV U_k , we impose the following flow-conservation

constraint

$$\sum_{i=0}^N \alpha_{i,(j,q)}^k = \sum_{l=1}^N \sum_{r=1}^{O_l} \alpha_{j,(l,r)}^k + \alpha_{j,(0,1)}^k, \quad \forall V_{j,q} \in \tilde{\mathcal{V}}, U_k \in \mathcal{U}, \quad (7)$$

where the left-hand side denotes the total number of incoming arcs to duplicated TP $V_{j,q}$ for UAV U_k , while the right-hand side denotes the total number of outgoing arcs from $V_{j,q}$, including the case where U_k returns from $V_{j,q}$ to its starting location. This constraint ensures that, whenever UAV U_k visits duplicated TP $V_{j,q}$, the corresponding route remains continuous. In addition, to eliminate disconnected cycles that do not belong to the main route of a UAV, we introduce visiting order variables $\pi_{j,q}^k$ and impose the following subtour-elimination constraint:

$$\pi_{j,q}^k - \pi_{l,r}^k + 1 \leq \tilde{N} (1 - \alpha_{j,(l,r)}^k), \quad \forall U_k \in \mathcal{U}, (j,q) \neq (l,r), \quad (8)$$

where $\pi_{j,q}^k$ denotes the visiting order of duplicated TP $V_{j,q}$ in the route of UAV U_k , and $\tilde{N} = \sum_{j=1}^N O_j$ is the total number of duplicated TPs. This constraint prevents the formation of disconnected subtours by enforcing a consistent visiting order among duplicated TPs connected by UAV U_k .

The ordering variables are further bounded by

$$1 \leq \pi_{j,q}^k \leq \tilde{N}, \quad \forall V_{j,q} \in \tilde{\mathcal{V}}, U_k \in \mathcal{U}. \quad (9)$$

where the lower and upper bounds define the feasible range of the visiting order for each duplicated TP in the route of UAV U_k .

The distance corresponding to UAV travel from TP V_i to TP V_j is denoted by $d_{i,j}$, and is defined as

$$d_{i,j} = \begin{cases} \|\mathbf{Q}_i - \mathbf{Q}_j\|_2, & \text{if } i \neq j, \\ M, & \text{if } i = j, \end{cases} \quad (10)$$

where $\mathbf{Q}_i$ and $\mathbf{Q}_j$ are the spatial coordinates of TPs V_i and V_j , respectively, and M is a sufficiently large constant used to penalize consecutive visits to the same TP.

B. Time Scheduling Model

In the resilient multi-UAV system, it is crucial to ensure that each UAV maintains a temporally consistent service trajectory while avoiding concurrent visits to the same physical target. Let $t_{i,q}^k$ denote the time at which UAV U_k arrives at or begins servicing the q -th instance of target V_i . Assume that the travel time for UAV U_k between targets V_i and V_j is denoted by $T_{i,j,k}^{\text{fly}}$, and that each target V_i may require a data processing time $T_{i,k}^{\text{data}}$ by UAV U_k , which is set to zero if no service is needed. When UAV U_k transitions from TP $V_{i,q}$ to TP $V_{j,r}$, i.e., $\alpha_{i,(j,r)}^k = 1$, the following temporal coupling constraint must be satisfied

$$t_{j,r}^k \geq t_{i,q}^k + T_{i,j,k}^{\text{fly}} + T_{i,k}^{\text{data}} - M(1 - \alpha_{i,(j,r)}^k). \quad (11)$$

Beyond ensuring temporal consistency across UAV transitions, sequential ordering is required for repeated visits to the same target to avoid service overlap. Let $t_{i,q}^{k_1}$ and $t_{i,q+1}^{k_2}$ denote the starting times of the q -th and $(q+1)$ -th visits to TP V_i , performed by UAV U_{k_1} and U_{k_2} , respectively. Let T_{i,k_1}^{data} be the

service duration at V_i for UAV U_{k_1} . The following constraint ensures proper temporal separation

$$t_{i,q}^{k_1} + T_{i,k_1}^{\text{data}} \leq t_{i,q+1}^{k_2}, \forall V_{i,q} \in \tilde{\mathcal{V}}. \quad (12)$$

It is worth noting that the proposed TARO framework operates at the mission-planning and resource-allocation layer. It focuses on UAV-TP association, repeated-visit scheduling, task offloading, and bandwidth allocation, while low-level flight stabilization and local obstacle/collision avoidance are assumed to be handled by onboard flight-control and sense-and-avoid modules. Therefore, the temporal conflict-avoidance constraint considered in this work is intended to prevent service overlap at the same physical TP, rather than to model continuous-space mid-air collision avoidance among UAVs during flight.

C. Data Processing Model

According to the 3GPP technical report on enhanced LTE support for aerial vehicles [64], UAV-to-ground links can achieve a high probability of line-of-sight (LoS) propagation when UAVs operate at sufficiently high altitudes, e.g., above about 40 m in rural scenarios and 100 m in urban scenarios. Therefore, since the UAVs in this work fly at a fixed altitude and communicate with the BS through air-to-ground links, the wireless channel between the UAVs and the BS is assumed to be LoS-dominated. Following the commonly adopted UAV-assisted MEC channel model [65], we model the channel as a quasi-static LoS block-fading channel, where the channel remains constant within each fading block and the channel gain is primarily determined by distance-dependent path loss. Accordingly, the channel gain between UAV U_k and the BS, when associated with TP V_i , is expressed as

$$h_i = \frac{\beta_0}{d_i^2} = \frac{\beta_0}{H^2 + \|\mathbf{Q}_i - \mathbf{Q}_{\text{BS}}\|_2^2}, U_k \in \mathcal{U}, V_i \in \mathcal{V}, \quad (13)$$

where β_0 denotes the reference channel power gain measured at a specified reference distance, and d_i is the 3D distance between the UAV and the BS. According to Shannon's capacity theorem, the achievable data transmission rate (in bits per second) from UAV U_k to the BS, when performing tasks at TP V_i , is given by

$$r_{i,k} = b_k \log_2 \left(1 + \frac{P_k h_i}{\sigma^2} \right), U_k \in \mathcal{U}, V_i \in \mathcal{V}, \quad (14)$$

where b_k denotes the bandwidth allocated to UAV U_k , P_k is the transmit power of U_k , and σ^2 is the noise power at the receiver. To ensure fair and efficient utilization of spectral resources, the bandwidth allocation must satisfy the following constraint

$$\sum_{k=1}^K b_k \leq B, \quad (15)$$

where B is the total bandwidth available in the system.

D. Task Time Model

The travel time for UAV U_k to fly from TP V_i to TP V_j can be expressed as

$$T_{i,j,k}^{\text{fly}} = \frac{d_{i,j}}{v_k}, \quad (16)$$

where v_k is the flight speed of UAV U_k . Based on the travel time defined in Eq. (16), the total flight time of UAV U_k is computed as

$$T_k^{\text{fly}} = \sum_{i=0}^N \sum_{j=0}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k T_{i,j,k}^{\text{fly}}. \quad (17)$$

Transmission delay is a key quality-of-service (QoS) metric in UAV-assisted networks. When UAV U_k offloads a portion of a computational task to the BS, the total transmission time T_k^{tra} can be expressed as

$$T_k^{\text{tra}} = \sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k \frac{\lambda_{j,k} D_j}{r_{j,k}}, U_k \in \mathcal{U}, \quad (18)$$

where D_j denotes the data size of the computational task associated with TP V_j , and $\lambda_{j,k}$ represents the fraction of the task that UAV U_k offloads to the BS. The remaining portion $(1 - \lambda_{j,k})$ is processed locally onboard the UAV. The offloading ratio is constrained by

$$0 \leq \lambda_{j,k} \leq 1, U_k \in \mathcal{U}, V_j \in \mathcal{V}. \quad (19)$$

The local computation time T_k^{com} incurred by UAV U_k when processing tasks onboard is given by

$$T_k^{\text{com}} = \sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k \frac{(1 - \lambda_{j,k}) D_j \theta}{F_k}, U_k \in \mathcal{U}, \quad (20)$$

where F_k denotes the CPU frequency of UAV U_k and θ is the number of CPU cycles required to process one bit of data. To facilitate integration with the time scheduling constraints, we define the effective service delay T_i^k at TP V_i for UAV U_k as

$$T_{i,k}^{\text{data}} = \max \left\{ \frac{\lambda_{i,k} D_i}{r_{i,k}}, \frac{(1 - \lambda_{i,k}) D_i \theta}{F_k} \right\}. \quad (21)$$

Using Eq. (18) and (20), the total data processing time T_k^{data} for UAV U_k is given by

$$T_k^{\text{data}} = \sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k T_{j,k}^{\text{data}}. \quad (22)$$

By combining the data processing time with the flight time, the overall task completion time T_k^{total} for UAV U_k is given by

$$T_k^{\text{total}} = T_k^{\text{fly}} + T_k^{\text{data}}, \quad (23)$$

which represents the total duration required for UAV U_k to complete its assigned mission, including flying, computation, and transmission phases.

E. Problem Formulation

Our objective is to minimize the maximum task completion time T_k^{total} across all UAVs by jointly optimizing the UAV-TP association $\mathcal{A} = \{\alpha_{i,(j,q)}^k, \forall i, j, k, q\}$, the visiting order variable $\pi = \{\pi_{j,q}^k, \forall j, q, k\}$ the task assignment decisions $\lambda = \{\lambda_{j,k}, \forall j, k\}$, the bandwidth allocation $\mathcal{B} = \{b_k, \forall k\}$,

and the time scheduling variable $\mathbf{t} = \{t_{i,q}^k, \forall i, q, k\}$. The problem can be formulated as follows

$$\mathcal{P}_1 : \min_{\mathcal{A}, \pi, \lambda, \mathcal{B}, \mathbf{t}} \max_k T_k^{\text{total}}$$

$$\text{s.t.} \quad \sum_{k=1}^K \sum_{i=0}^N \alpha_{i,(j,q)}^k = 1, \quad (24a)$$

$$\sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k \leq L_k, \quad (24b)$$

$$\sum_{i=0}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k \leq 1, \quad (24c)$$

$$\sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{0,(j,q)}^k = 1, \quad (24d)$$

$$\sum_{i=1}^N \alpha_{i,(0,1)}^k = 1, \quad (24e)$$

$$\pi_{j,q}^k - \pi_{l,r}^k + 1 \leq \tilde{N}(1 - \alpha_{j,(l,r)}^k), \quad (24f)$$

$$1 \leq \pi_{j,q}^k \leq \tilde{N}, \quad (24g)$$

$$t_{j,r}^k \geq t_{i,q}^k + T_{i,j,k}^{\text{fly}} + T_{i,k}^{\text{data}} - M(1 - \alpha_{i,(j,r)}^k), \quad (24h)$$

$$t_{i,q}^{k_1} + T_{i,k_1}^{\text{data}} \leq t_{i,q+1}^{k_2}, \quad (24i)$$

$$\sum_{k=1}^K b_k \leq B, \quad (24j)$$

$$\alpha_{i,(j,q)}^k \in \{0, 1\}, \quad (24k)$$

$$0 \leq \lambda_{j,k} \leq 1, \quad (24l)$$

$$\sum_{i=0}^N \alpha_{i,(j,q)}^k = \sum_{l=1}^N \sum_{r=1}^{O_l} \alpha_{j,(l,r)}^k + \alpha_{j,(0,1)}^k. \quad (24m)$$

Constraints (24a)-(24e) and (24k) define the UAV-TP association and routing logic, ensuring unique task coverage, UAV capacity limits, and proper route initiation and termination. Constraints (24f) and (24g) are introduced to eliminate sub-tours based on node ordering, thereby excluding disconnected cycles and ensuring that the duplicated TPs assigned to each UAV form a single connected route. Constraint (24h) enforces time feasibility between successive tasks, while (24i) enforces temporal separation between repeated visits to the same physical TP, thereby avoiding service overlap at that TP. Constraint (24j) ensures that total bandwidth remains within the system budget. Finally, (24l) bounds the offloading ratio within $[0, 1]$, allowing flexible task distribution between local and remote processing.

IV. SOLUTION ALGORITHM

Solving Problem $\mathcal{P}_1$ is challenging due to its mixed-integer nonlinear structure, which involves both discrete and continuous decision variables. The problem is NP-hard because it requires combinatorial UAV routing and handles nonconvex constraints related to time and resource allocation. Therefore, in this section, we adopt a Benders-inspired decomposition

framework with infeasibility elimination to partition Problem $\mathcal{P}_1$ into a routing master problem and two continuous subproblems [66]. A simple alternating optimization strategy is insufficient in the present problem setting. In particular, under repeated TP visits, a routing and assignment solution that appears favorable at the master-search level may still become infeasible after time-scheduling verification due to temporal overlap among repeated visits to the same physical TP. Therefore, infeasible routing patterns must be identified and excluded during the search process. The overall solution is obtained by iteratively solving these components, where the master problem determines the routing and scheduling decisions, and the subproblems handle the continuous optimization of offloading and bandwidth allocation.

A. Master Problem: UAV-TP Assignment Optimization with TP Resilience Level and Temporal Conflict Avoidance

Given a set of offloading decisions λ , the visiting order variable π and bandwidth allocation $\mathcal{B}$, we first optimize UAV-TP association $\mathcal{A}$ and time scheduling variables $\mathbf{t}$. This step determines the discrete assignment and temporal coordination based on the TP resilience level requirements and temporal conflict-avoidance constraints, and forms the upper-level decision layer in the decomposition framework. The resulting master problem is formulated as follows

$$\mathcal{P}_2 : \min_{\mathcal{A}, \pi, \mathbf{t}} \max_k T_k^{\text{total}} \\ \text{s.t.} \quad (24a) - (24i), (24k).$$

The master problem $\mathcal{P}_2$ can be regarded as a variant of the multi-traveling salesman problem (mTSP), augmented with temporal coupling and precedence constraints arising from TP duplication and temporal conflict avoidance. Due to the combinatorial nature of the routing variables, the enforcement of temporal feasibility, and the need for coordination among multiple UAVs, the problem is computationally intractable and classified as NP-hard. To address this, an exact algorithm based on the branch and bound (B&B) and a heuristic algorithm are proposed respectively in what follows.

1) Exact Algorithm: The B&B algorithm explores the UAV-TPs assignment space by incrementally constructing partial solutions through recursive branching. At each level of the search tree, a duplicate TP $V_i \in \mathcal{V}$ is assigned to a UAV $U_k \in \mathcal{U}$, forming a partial assignment $\mathcal{A}_{\text{partial}}$. Let $\mathcal{S}_k$ denote the set of duplicate TPs currently assigned to UAV U_k in $\mathcal{A}_{\text{partial}}$. The complete solution space is thus explored by evaluating all valid extensions of $\mathcal{A}_{\text{partial}}$.

To improve computational efficiency, the B&B algorithm employs upper and lower bounds on the objective value to guide pruning. At each search TP, a lower bound estimates the best achievable outcome from the partial solution, while a feasible upper bound limits the exploration to promising branches only.

Upper Bound: An initial feasible solution is first obtained using the heuristic algorithm in Algorithm 2 to initialize the upper bound $\bar{T}$ on the makespan. Specifically, the heuristic algorithm starts from a greedy assignment, generates neighboring solutions by exchanging duplicated TPs among UAV

routes, and discards any candidate solution that violates the route-capacity constraint or the temporal conflict-avoidance condition. Denote the resulting initial feasible solution as $(\mathcal{A}^{\text{init}}, \pi^{\text{init}}, t^{\text{init}})$. The corresponding upper bound is defined as

$$\bar{T} = \max_{k \in \mathcal{U}} T_k(\mathcal{A}^{\text{init}}, \pi^{\text{init}}, t^{\text{init}}), \quad (26)$$

where $T_k(\mathcal{A}^{\text{init}}, \pi^{\text{init}}, t^{\text{init}})$ denotes the completion time of UAV U_k under the initial feasible solution. This bound is used to discard partial solutions whose lower bounds exceed $\bar{T}$.

Lower Bound: For the master problem $\mathcal{P}_2$, the offloading decisions λ and bandwidth allocation $\mathcal{B}$ are fixed. Hence, $T_{j,k}^{\text{data}}$ is known for each duplicated TP $V_{j,q}$ and UAV U_k . During the B&B search, let $\mathcal{A}_{\text{partial}}$ denote the current partial assignment, where only a subset of duplicated TPs has been assigned to UAVs. Let $\mathcal{S}_k$ be the set of duplicated TPs already assigned to UAV U_k in $\mathcal{A}_{\text{partial}}$, and let

$$\mathcal{S}_{\text{rem}} = \tilde{\mathcal{V}} \setminus \bigcup_{k=1}^K \mathcal{S}_k \quad (27)$$

denote the set of unassigned duplicated TPs. Define

$$T_{k,\text{cur}}^{\text{data}} = \sum_{V_{j,q} \in \mathcal{S}_k} T_{j,k}^{\text{data}}, \quad \underline{T}_{j,q}^{\text{data}} = \min_{k \in \mathcal{U}} T_{j,k}^{\text{data}}, \quad \forall V_{j,q} \in \mathcal{S}_{\text{rem}}. \quad (28)$$

A valid lower bound on the objective value of any feasible full extension of $\mathcal{A}_{\text{partial}}$ is

$$\underline{T} = \max \left\{ \max_{k \in \mathcal{U}} T_{k,\text{cur}}^{\text{data}}, \frac{\sum_{k=1}^K T_{k,\text{cur}}^{\text{data}} + \sum_{V_{j,q} \in \mathcal{S}_{\text{rem}}} \underline{T}_{j,q}^{\text{data}}}{K} \right\}. \quad (29)$$

Lemma 1. *Every feasible full extension of the current partial assignment $\mathcal{A}_{\text{partial}}$ satisfies $T \geq \underline{T}$, where $\underline{T}$ is given by (29).*

Proof. For any feasible full extension of $\mathcal{A}_{\text{partial}}$, the completion time of each UAV satisfies

$$T_k^{\text{total}} = T_k^{\text{fly}} + T_k^{\text{data}} \geq T_k^{\text{data}} \geq T_{k,\text{cur}}^{\text{data}}, \quad \forall k \in \mathcal{U}, \quad (30)$$

since the duplicated TPs in $\mathcal{S}_k$ have already been assigned to UAV U_k . Hence,

$$T = \max_{k \in \mathcal{U}} T_k^{\text{total}} \geq \max_{k \in \mathcal{U}} T_{k,\text{cur}}^{\text{data}}. \quad (31)$$

Moreover, each unassigned duplicated TP $V_{j,q} \in \mathcal{S}_{\text{rem}}$ must eventually be assigned to one UAV, and thus contributes at least $\underline{T}_{j,q}^{\text{data}}$. Therefore,

$$\sum_{k=1}^K T_k^{\text{total}} \geq \sum_{k=1}^K T_{k,\text{cur}}^{\text{data}} + \sum_{V_{j,q} \in \mathcal{S}_{\text{rem}}} \underline{T}_{j,q}^{\text{data}}. \quad (32)$$

Using

$$\max_{k \in \mathcal{U}} T_k^{\text{total}} \geq \frac{1}{K} \sum_{k=1}^K T_k^{\text{total}}, \quad (33)$$

we obtain

$$T \geq \frac{\sum_{k=1}^K T_{k,\text{cur}}^{\text{data}} + \sum_{V_{j,q} \in \mathcal{S}_{\text{rem}}} \underline{T}_{j,q}^{\text{data}}}{K}. \quad (34)$$

Combining the above inequalities gives $T \geq \underline{T}$. $\square$

Algorithm 1 Branch and Bound Algorithm for Problem $\mathcal{P}_2$

Input: $\lambda, \mathcal{B}$.

```

1: Initialization: Generate initial solution  $\mathcal{A}^{\text{init}}$ , set upper bound  $T^* \leftarrow \bar{T}$  according to Algorithm 2, and set  $\{\mathcal{S}_k\} \leftarrow \emptyset$ .
2: Define Function DFS( $i$ ):
3: if  $i > \tilde{N}$  then
4:   Construct complete solution  $\mathcal{A}$ , check feasibility and temporal conflicts, and update  $T^*$  if improved.
5: return
6: end if
7: for each UAV  $k = 1$  to  $K$  do
8:    $\mathcal{S}_k \leftarrow \mathcal{S}_k \cup \{V_i\}$ .
9:   if assigning TP  $V_i$  to UAV  $k$  is valid then
10:    Estimate lower bound  $\underline{T}$  of current partial assignment.
11:    if  $\underline{T} < T^*$  then
12:      DFS( $i + 1$ )
13:    end if
14:  end if
15:   $\mathcal{S}_k \leftarrow \mathcal{S}_k \setminus \{V_i\}$ .
16: end for
17: End Function DFS( $i$ ).
18: Start: DFS(1).
Output:  $\mathcal{A}^*, \pi^*$ .

```

2) Heuristic Algorithm: In addition, to accelerate the convergence of the B&B algorithm, we propose a heuristic algorithm with reduced computational complexity to efficiently approximate the solution to Problem $\mathcal{P}_2$ (see Algorithm 2). While it does not guarantee the global optimality, the heuristic algorithm provides fast convergence and strong scalability, making it well-suited for large-scale instances where exact methods become computationally prohibitive.

To efficiently approximate the solution to problem $\mathcal{P}_2$, the heuristic algorithm incorporates several strategic mechanisms aimed at enhancing both solution feasibility and the overall effectiveness of the search process:

- In each iteration, neighboring solutions are generated by exchanging a duplicate TP between two UAV routes.
- A tabu list maintains a record of recently executed moves to prevent their immediate reconsideration, thereby promoting exploration of new regions in the solution space.
- If no improvement is observed over a predefined number of iterations, the current solution is reconstructed by randomly reassigning TPs, while ensuring that all feasibility constraints are satisfied.
- The initial solution is constructed using a greedy approach that avoids temporal conflicts on shared physical TPs. If any conflicts are detected, a repair procedure is subsequently applied to restore feasibility.

B. Subproblem I: Task Offloading Decisions Optimization

With a determined UAV-TP association $\mathcal{A}$ and bandwidth allocation $\mathcal{B}$, we then focus on optimizing the task offloading decisions λ . The offloading subproblem is reformulated in

Algorithm 2 Heuristic Algorithm for Problem $\mathcal{P}_2$

Input: $\lambda, \mathcal{B}$.

- 1: **Initialization:** Set maximum iteration index $\tau_{\max}$, restart threshold C_{restart} , tabu list $\mathcal{J} \leftarrow \emptyset$, no-improvement counter $c \leftarrow 0$, generate $\mathcal{A}^{(0)}$ by greedy method.
 - 2: **Calculate:** Total time T_{temp} according to $\mathcal{A}^{(0)}$.
 - 3: **repeat**
 - 4: Generate neighbor solutions by exchanging duplicate TP between two UAV routes in $\mathcal{A}^{r-1}$.
 - 5: Discard any $\mathcal{A}$ such that $\delta = 1$ or constraint (24b) is violated.
 - 6: Select the best neighbor solution $\mathcal{A}^{(r)}$ with the smallest makespan T_{temp} .
 - 7: Update $\mathcal{A} \leftarrow \mathcal{A}^{(r)}$, and record the move in $\mathcal{J}$.
 - 8: **if** $T_{\text{temp}} < T_{\text{best}}$ **then**
 - 9: Update $\mathcal{A}^* \leftarrow \mathcal{A}^{(r)}$, $T_{\text{best}} \leftarrow T_{\text{temp}}$, $c \leftarrow 0$.
 - 10: **else**
 - 11: $c \leftarrow c + 1$.
 - 12: **end if**
 - 13: **if** $c \geq C_{\text{restart}}$ **then**
 - 14: Reconstruct $\mathcal{A}$ randomly while satisfying constraints; reset $\mathcal{J} \leftarrow \emptyset$, $c \leftarrow 0$.
 - 15: **end if**
 - 16: Update $\tau \leftarrow \tau + 1$
 - 17: **until** $\tau > \tau_{\max}$.
- Output:** $\mathcal{A}^*, \pi^*$.
-

a form consistent with the per-task data processing time definition in (21). Define

$$a_{j,k} \triangleq \frac{D_j}{r_{j,k}}, \quad c_{j,k} \triangleq \frac{D_j \theta}{F_k}. \quad (35)$$

And further define

$$g_{j,k}(\lambda_{j,k}) \triangleq \max \{a_{j,k} \lambda_{j,k}, c_{j,k} (1 - \lambda_{j,k})\}, \quad (36)$$

where $a_{j,k} \lambda_{j,k}$ denotes the transmission delay of the offloaded part, while $c_{j,k} (1 - \lambda_{j,k})$ denotes the local computation delay of the remaining part. Therefore, $g_{j,k}(\lambda_{j,k})$ exactly represents the per-task data processing time defined in (21). Accordingly, for a given assignment $\mathcal{A}$, the total data processing time of UAV U_k can be written as

$$T_k^{\text{data}} = \sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k g_{j,k}(\lambda_{j,k}). \quad (37)$$

Then, the offloading subproblem can be reformulated as

$$\begin{aligned} \mathcal{P}_3 : \min_{\lambda} \quad & \max_k \left(T_k^{\text{fly}} + \sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k g_{j,k}(\lambda_{j,k}) \right) \\ \text{s.t.} \quad & 0 \leq \lambda_{j,k} \leq 1. \end{aligned} \quad (38a)$$

To further convert the above min-max problem into a standard convex form, we introduce an auxiliary variable μ and epigraph variables $\xi_{j,k}$. Then, Problem $\mathcal{P}_3$ can be equivalently transformed into

$$\mathcal{P}_4 : \min_{\lambda, \xi, \mu} \quad \mu$$

$$\text{s.t.} \quad T_k^{\text{fly}} + \sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \alpha_{i,(j,q)}^k \xi_{j,k} \leq \mu, \quad (39a)$$

$$\xi_{j,k} \geq a_{j,k} \lambda_{j,k}, \quad \forall j, k, \quad (39b)$$

$$\xi_{j,k} \geq c_{j,k} (1 - \lambda_{j,k}), \quad \forall j, k, \quad (39c)$$

$$0 \leq \lambda_{j,k} \leq 1, \quad \forall j, k. \quad (39d)$$

It can be verified that $\mathcal{P}_4$ is a convex optimization problem, since the objective is linear and all constraints are affine. Thus, it can be efficiently solved using standard convex optimization solvers such as CVX. Moreover, by analyzing the Karush-Kuhn-Tucker (KKT) conditions, the following closed-form solution for the optimal offloading ratio can be obtained.

Theorem 1. *Given fixed UAV-TP association $\mathcal{A}$ and bandwidth allocation $\mathcal{B}$, the optimal offloading ratio $\lambda_{j,k}^*$ that minimizes the maximum processing delay is:*

$$\lambda_{j,k}^* = \frac{c_{j,k}}{a_{j,k} + c_{j,k}}, \quad (40)$$

where $a_{j,k} = \frac{D_j}{r_{j,k}}$ and $c_{j,k} = \frac{D_j \theta}{F_k}$.

Proof. See Appendix A. $\square$

C. Subproblem II: Bandwidth Allocation Optimization

Finally, with the given UAV-TP association $\mathcal{A}$ and offloading decisions λ , we optimize the bandwidth allocation

$$\begin{aligned} \mathcal{P}_5 : \min_{\mathcal{B}} \quad & \max_k T_k^{\text{total}} \\ \text{s.t.} \quad & \sum_{k=1}^K b_k \leq B. \end{aligned} \quad (41a)$$

Since the transmission time is decreasing monotonically with respect to b_k , we can use a binary search to solve this problem [67]. The auxiliary variable μ is reused here, consistent with Subproblem I. Accordingly, the bandwidth allocation subproblem is formulated as follows

$$\mathcal{P}_6 : \min_{\mathcal{B}, \mu} \quad \mu$$

$$\text{s.t.} \quad T_k^{\text{tra}} \leq \mu - T_k^{\text{fly}}, \quad (42a)$$

$$T_k^{\text{com}} \leq \mu - T_k^{\text{fly}}, \quad (42b)$$

$$\sum_{k=1}^K b_k \leq B, \quad U_k \in \mathcal{U}. \quad (42c)$$

Lemma 2. *For a given value of μ , the minimum bandwidth required for UAV U_k to satisfy the transmission constraint can be computed as*

$$b_k^{\min}(\mu) = \frac{1}{\mu - T_k^{\text{fly}}} \sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \frac{\alpha_{i,(j,q)}^k \lambda_{j,k} D_j}{\log_2 \left(1 + \frac{P_k h_{j,i}}{\sigma^2} \right)}. \quad (43)$$

Proof: Define $M_k \triangleq \sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{O_j} \frac{\alpha_{i,(j,q)}^k \lambda_{j,k} D_j}{\log_2 \left(1 + \frac{P_k h_{j,i}}{\sigma^2} \right)}$.

According to (42a), we require $\frac{M_k}{b_k} \leq \mu - T_k^{\text{fly}}$, which yields $b_k \geq \frac{M_k}{\mu - T_k^{\text{fly}}}$. Thus, the minimum bandwidth is $b_k^{\min}(\mu) = \frac{M_k}{\mu - T_k^{\text{fly}}}$.

Assume a bandwidth $b'_k < b_k^{\min}(\mu)$ satisfies the constraint. Then, $T_k^{\text{tra}} = \frac{M_k}{b'_k} > \frac{M_k}{b_k^{\min}(\mu)} = \mu - T_k^{\text{fly}}$, which contradicts the constraint. Therefore, $b_k^{\min}(\mu)$ is indeed the minimum required bandwidth. $\square$

The binary search algorithm is outlined as Algorithm 3.

Algorithm 3 Binary Search for Problem $\mathcal{P}_6$

Input: $\mathcal{A}, \lambda$.

- 1: Initialize $\mu_{\min} = \max_k \{T_k^{\text{fly}} + T_k^{\text{com}}\}$, and set a sufficiently large $\mu_{\max}$.
- 2: **repeat**
- 3: Compute $\mu = \frac{\mu_{\min} + \mu_{\max}}{2}$.
- 4: **for** $k = 1$ to K **do**
- 5: Compute required bandwidth $b_k = b_k^{\min}(\mu)$ using Eq. (43).
- 6: **end for**
- 7: **if** $\sum_{k=1}^K b_k > B$ **then**
- 8: $\mu_{\min} = \mu$
- 9: **else**
- 10: $\mu_{\max} = \mu$
- 11: **end if**
- 12: **until** $\mu_{\max} - \mu_{\min} \leq \epsilon$
- 13: Update $\mu^* = \mu_{\max}$, $\mathcal{B}^* = \{b_k^{\min}(\mu^*)\}$.

Output: $\mathcal{B}^*$.

D. Overall Algorithm, Convergence, and Complexity Analysis

We propose the TARO algorithm for solving Problem $\mathcal{P}_1$, where the UAV-TP association $\mathcal{A}$ and time scheduling $\mathbf{t}$ are optimized in the master problem, and the offloading decisions λ and bandwidth allocation $\mathcal{B}$ are optimized in the subproblems. The steps are detailed in Algorithm 4.

The convergence behavior of the proposed Benders-inspired iterative decomposition framework can be analyzed from the inner and outer iterations. Let $\Phi^{(r,s)}$ denote the objective value of the continuous subproblem in the s -th inner iteration of the r -th outer iteration. For fixed UAV-TP assignment and time scheduling decisions, the offloading ratio and bandwidth allocation are alternately updated by solving their corresponding subproblems. Since each update does not increase the objective value, we have

$$\Phi^{(r,s+1)} \leq \Phi^{(r,s)}. \quad (44)$$

Moreover, $\Phi^{(r,s)}$ is lower bounded by zero. Therefore, the inner loop converges in terms of the objective value. For the outer iteration, let $T^{(r)}$ denote the incumbent maximum completion time after the r -th iteration. The incumbent solution is updated only when a better feasible solution is found, i.e.,

$$T^{(r+1)} = \min \left\{ T^{(r)}, \hat{T}^{(r+1)} \right\} \leq T^{(r)}, \quad (45)$$

where $\hat{T}^{(r+1)}$ is the objective value obtained in the current outer iteration. Hence, the incumbent objective value is monotonically non-increasing. Since the number of possible UAV-TP assignment patterns is finite and a maximum number of outer iterations is imposed, the proposed framework terminates in a finite number of iterations.

Algorithm 4 TARO Algorithm for Solving Problem $\mathcal{P}_1$

Input: UAV-TP assignment $\mathcal{A}^{(0)}$, time scheduling variable $\mathbf{t}^{(0)}$, offloading decisions $\lambda^{(0,0)}$, bandwidth allocation $\mathcal{B}^{(0,0)}$, iteration limits $\tau_{\text{out}}^{\max}$ and $\tau_{\text{in}}^{\max}$, tolerances ϵ_{in} and ϵ_{out} , and initial best time $\eta^{(0)}$.

- 1: **Initialization:** Set iteration index $\tau_{\text{out}} = 0$, tolerance ϵ , and initialize feasibility cut set $\mathcal{C}_{\text{feas}} \leftarrow \emptyset$.
- 2: **repeat**
- 3: Solve master problem $\mathcal{P}_2$ using Algorithm 1 to obtain $\mathcal{A}^{(\tau_{\text{out}})}, \mathbf{t}^{(\tau_{\text{out}})}$.
- 4: Initialize $\lambda^{(\tau_{\text{out}},0)}, \mathcal{B}^{(\tau_{\text{out}},0)}$, set $\tau_{\text{in}} = 0$.
- 5: **repeat**
- 6: Update $\lambda^{(\tau_{\text{out}},\tau_{\text{in}}+1)}$ using the closed-form solution of $\mathcal{P}_4$.
- 7: Update $\mathcal{B}^{(\tau_{\text{out}},\tau_{\text{in}}+1)}$ using the binary search in Algorithm 3.
- 8: $\tau_{\text{in}} \leftarrow \tau_{\text{in}} + 1$
- 9: **until** $\frac{\|\lambda^{(\tau_{\text{out}},\tau_{\text{in}})} - \lambda^{(\tau_{\text{out}},\tau_{\text{in}}-1)}\|_F}{\max\{1, \|\lambda^{(\tau_{\text{out}},\tau_{\text{in}}-1)}\|_F\}} \leq \epsilon_{\text{in}}$ and $\frac{\|\mathcal{B}^{(\tau_{\text{out}},\tau_{\text{in}})} - \mathcal{B}^{(\tau_{\text{out}},\tau_{\text{in}}-1)}\|_2}{\max\{1, \|\mathcal{B}^{(\tau_{\text{out}},\tau_{\text{in}}-1)}\|_2\}} \leq \epsilon_{\text{in}}$, or $\tau_{\text{in}} \geq \tau_{\text{in}}^{\max}$.
- 10: **if** feasible solution is obtained **then**
- 11: Compute total time $\eta^{(\tau_{\text{out}})} = \max_k T_k^{k,\text{total}}$.
- 12: Update best solution if $\eta^{(\tau_{\text{out}})}$ improves.
- 13: **else**
- 14: Generate and add feasibility cut to $\mathcal{C}_{\text{feas}}$.
- 15: **end if**
- 16: $\tau_{\text{out}} \leftarrow \tau_{\text{out}} + 1$
- 17: **until** $\tau_{\text{out}} \geq \tau_{\text{out}}^{\max}$ or $\frac{|\eta_{\text{best}}^{(\tau_{\text{out}})} - \eta_{\text{best}}^{(\tau_{\text{out}}-1)}|}{\max\{1, \eta_{\text{best}}^{(\tau_{\text{out}}-1)}\}} \leq \epsilon_{\text{out}}$.

Output: $\mathcal{A}^*, \mathbf{t}^*, \lambda^*, \mathcal{B}^*$

The computational complexity of the proposed TARO algorithm mainly comes from the master problem and the two continuous subproblems. Let K denote the number of UAVs and $\tilde{N} = \sum_{j=1}^N O_j$ the total number of duplicated TPs introduced by the resilience requirement. For the master problem $\mathcal{P}_2$, when the exact branch-and-bound method is adopted, the search tree has depth $\tilde{N}$, and each duplicated TP can be assigned to one of the K UAVs at each branching step. Therefore, the worst-case complexity grows exponentially with the number of duplicated TPs and is given by $\mathcal{O}(K^{\tilde{N}})$. The exact branch-and-bound solver is mainly suitable for small-to medium-scale problem instances. When the number of duplicated TPs becomes large, the heuristic master-problem solver provides a more scalable alternative with significantly lower computational burden. When the heuristic algorithm is adopted for $\mathcal{P}_2$, neighboring solutions are generated by exchanging duplicated TPs among UAV routes. The corresponding complexity is $\mathcal{O}(\tilde{N}^2)$. For the offloading subproblem $\mathcal{P}_4$, the offloading ratios of all UAV-TP pairs can be updated independently with complexity $\mathcal{O}(K\tilde{N})$. For the bandwidth allocation subproblem $\mathcal{P}_6$, the bandwidth variables of all UAVs are updated with complexity $\mathcal{O}(K)$. Since the outer and inner iteration numbers of TARO are treated as constants with respect to the problem size, the overall complexity can be expressed as the sum of the above components. Accordingly, the overall computational complexity of the proposed TARO

TABLE II
SIMULATION PARAMETERS SETTING

Parameter	Value	Parameter	Value
H	20 m	β_0	-50 dB
B	20 MHz	θ	1000
L_k	[10,10,10]	σ^2	-110 dBm
v_k	[10,15,25] m/s	$\mathbf{Q}_{BS}$	(500, 500)
F_k	[1.2,1.6,1.5] GHz	$\mathbf{Q}_k^{\text{start}}$	(500, 500)
P_k	[0.2,0.3,0.2] W	D_j	(0.1, 0.2] Gb

algorithm can be expressed as

$$\mathcal{O} = \begin{cases} \mathcal{O}(K\tilde{N} + K\tilde{N} + K), \text{exact master-problem solver,} \\ \mathcal{O}(\tilde{N}^2 + K\tilde{N} + K), \text{heuristic master-problem solver.} \end{cases} \quad (46)$$

V. SIMULATION RESULTS

A. Simulation Setup

We consider a simulation scenario involving 3 UAVs, 8 TPs, and a single BS positioned at coordinates (500, 500). The TPs are randomly positioned within a 1000 m $\times$ 1000 m square area. This setup emulates a practical environment in which multiple UAVs cooperate to accomplish assigned tasks collaboratively. Each UAV begins at the same position $\mathbf{Q}_k^{\text{start}}$ and sequentially visits the TPs assigned to it, with optimized path planning and task offloading decisions. In the default simulation setup, all UAVs are initialized at the same starting location $\mathbf{Q}_k^{\text{start}}$ for fair comparison. This setting avoids additional performance differences caused by heterogeneous initial UAV positions, while the proposed formulation itself allows each UAV to have an individual starting location. Therefore, using the same starting location in the simulations does not affect the generality of the proposed method. To reflect task heterogeneity, we set the resilience level as follows: $O_1 = 2$, $O_2 = 2$, $O_8 = 3$, and the remaining TPs have $O_i = 1$. After completing their tasks, the UAVs return to the starting point. Unless stated, the default simulation parameters are shown in Table II.

We compare our proposed TARO algorithm with the following benchmark algorithms:

- Heuristic algorithm (HA): UAV-TP associations are efficiently handled using the Algorithm 2.
- All offloading method (AO): All data are offloaded to the MEC server.
- Partial offloading (PO): Fixed portion of the data (70%) is processed locally on the UAV, while the remaining 30% is offloaded to the MEC server for remote processing.
- Equal bandwidth method (EB): Bandwidth is equally allocated to UAVs.

B. Simulation Results

Fig. 2 shows the convergence behavior of the proposed algorithm. TARO reaches a stable task completion time within a few outer iterations. In comparison, the heuristic algorithm

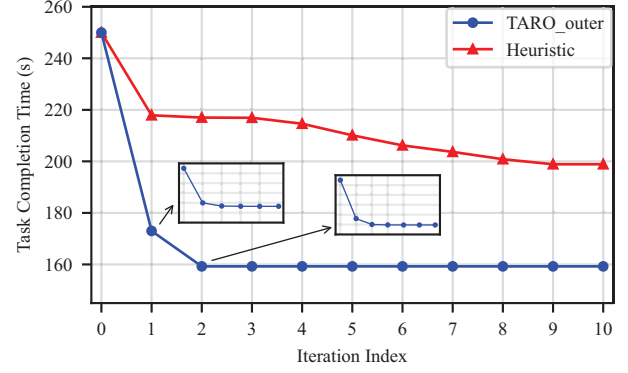
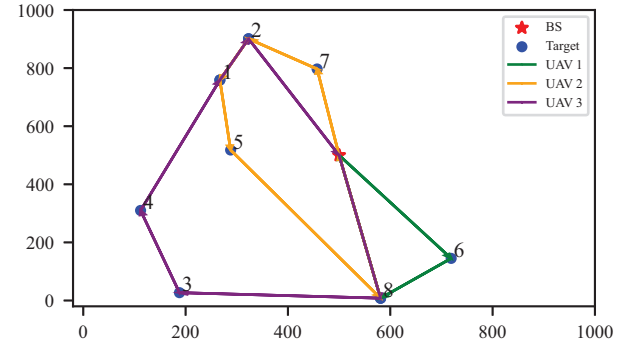
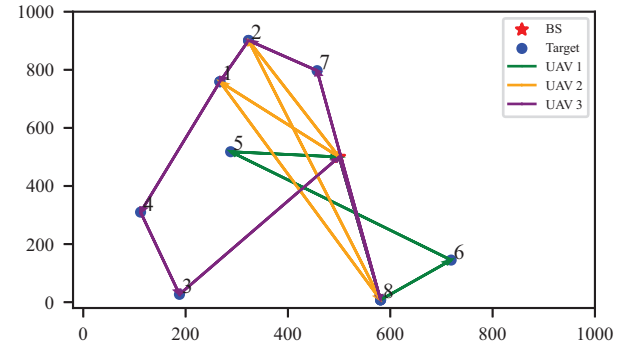


Fig. 2. Convergence performance comparison.



(a) TARO routes.

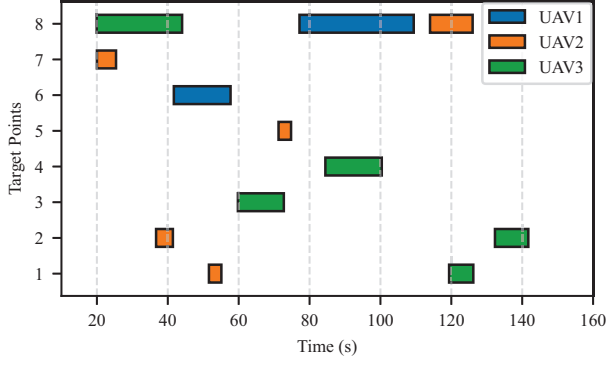


(b) HA routes.

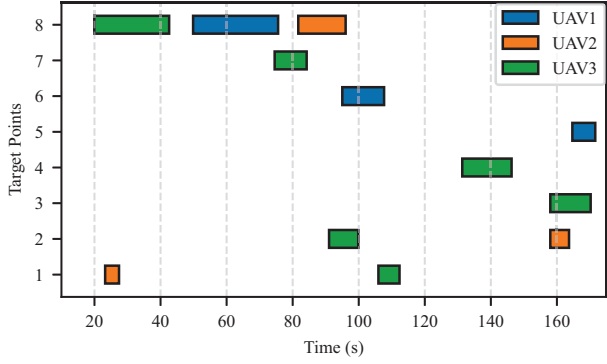
Fig. 3. Routes comparison.

completes more quickly in terms of runtime, but yields a slightly higher task completion time.

Fig. 3 compares the UAV-TP routes generated by TARO and HA. As shown in Fig. 3(a), TARO jointly optimizes UAV-TP assignment and route ordering, and tends to group spatially closer TPs into the same UAV route. This helps reduce unnecessary long-distance detours and balance the travel burden among UAVs. In contrast, Fig. 3(b) shows that HA may generate less compact routes, where some TPs are included in longer travel paths due to the lack of joint assignment and routing optimization. Therefore, TARO achieves a more coordinated route structure, which contributes to reducing

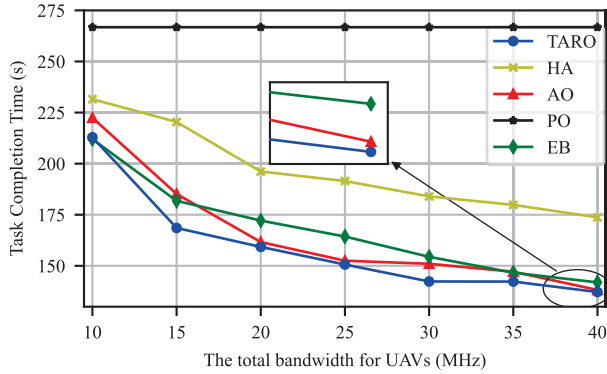


(a) TARO schedule.



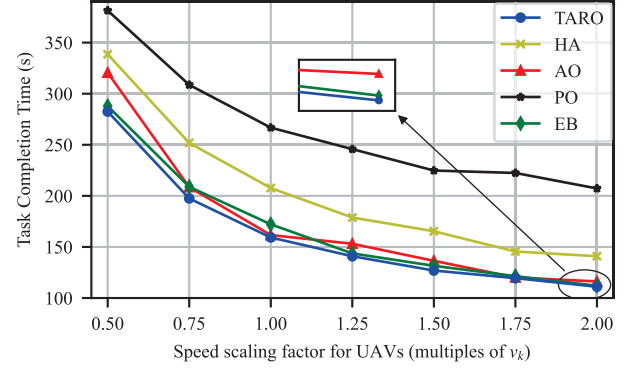
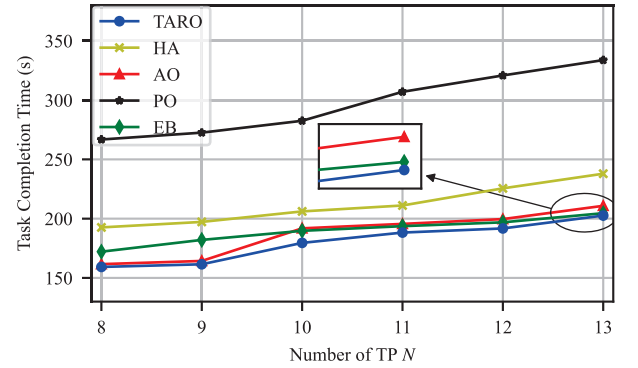
(b) HA schedule.

Fig. 4. Service schedule of UAVs over time for each assigned TP.

Fig. 5. Time versus the total bandwidth B for UAVs.

the overall flight distance and improving task completion efficiency.

Fig. 4 presents the service schedule of UAVs over time for each assigned target point. The repeated visits to the same physical targets by different UAVs are temporally separated, preventing simultaneous visit. The task executions are distributed along the timeline, and the service sequences vary across UAVs due to the combined effects of routing and time coordination. Compared with the heuristic baseline, the proposed TARO algorithm achieves a more compact scheduling pattern, reduces idle periods among UAVs, and ensures that

Fig. 6. Time versus speed scaling factor (multiples of v_k) for UAVs.Fig. 7. Time versus different number of TPs N .

the overall makespan is significantly shortened.

Fig. 5 shows the effect of total bandwidth on the maximum task completion time. TARO achieves the lowest completion time across all bandwidth levels. As bandwidth increases, the performance of the AO method improves and approaches that of TARO, as more data can be offloaded. The PO curve appears nearly flat because the fixed offloading ratio makes local computation the dominant bottleneck, and increasing bandwidth only reduces transmission delay without significantly reducing the overall task time. The EB method shows limited improvement due to uniform bandwidth allocation. The heuristic algorithm results in the highest completion time and exhibits little sensitivity to bandwidth variations.

Fig. 6 shows the impact of UAV speed scaling on the maximum task completion time. As the UAV speed increases, all algorithms exhibit a reduction in total completion time due to shorter travel durations. TARO maintains the lowest completion time across all speed levels. The performance of AO improves as faster UAVs reduce travel delays, allowing offloaded tasks to complete sooner. PO and EB show moderate reductions, while the heuristic method remains the least efficient overall. The gap between different methods becomes smaller at higher speeds, as travel time becomes less dominant in total delay.

Fig. 7 investigates how the maximum task completion time varies as the number of target points increases from 8 to 16.

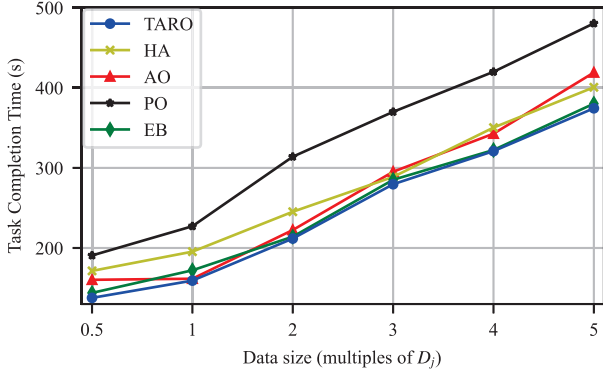


Fig. 8. Time versus Data size (multiples of D_j).

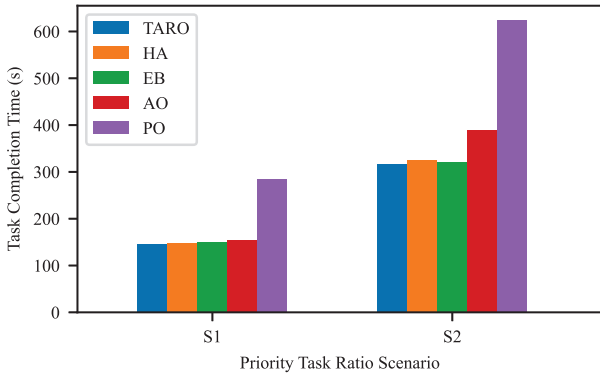


Fig. 9. Time versus resilience level O_i scenario for different schemes (S1: low-resilience level dominant, S2: high-resilience level dominant).

For all algorithms, the completion time rises with N because every additional target introduces extra travel and processing load. TARO consistently yields the lowest completion time across the entire range. AO benefits from the ability to offload more data when more targets are present, but still shows a steeper growth rate than TARO. PO and EB have intermediate performance, with EB limited by its uniform bandwidth allocation. The heuristic method exhibits the highest completion time and the most rapid increase, indicating limited scalability. However, its low computational complexity makes it more suitable for scenarios with strict real-time requirements. This also reflects the intended usage of the two solution strategies: the exact solver is adopted for moderate-scale instances where higher solution quality is desired, whereas the heuristic solver is better suited to larger-scale resilience-aware scenarios with many duplicated TPs or stricter real-time requirements.

Fig. 8 examines the impact of increasing data size on the maximum task completion time. As the data size grows, all algorithms experience a rising trend in completion time due to the increased computational and transmission burden. TARO achieves the shortest completion time across all data sizes. The EB scheme exhibits performance close to TARO, as its equal bandwidth allocation helps maintain stable transmission efficiency under heavier loads. AO ranks third, and its performance improves as more data can be offloaded to the MEC

server, reducing the local processing burden. PO and HA show steeper increases in completion time, with PO exhibiting the most rapid growth under large data sizes.

Fig. 9 illustrates the performance comparison of different algorithms under two types of task resilience level distributions, where scenario S1 is dominated by low resilience level tasks and scenario S2 is dominated by high resilience level tasks. In S1, where the majority of target points require only one visit, all algorithms yield comparable task completion times as the complexity of routing and inter UAV coordination is significantly reduced. In contrast, under scenario S2, TARO attains the shortest task completion time by jointly optimizing UAV to target point assignment, task offloading, and bandwidth allocation while fully accounting for task resilience level. The AO scheme exhibits degraded performance under repeated visit requirements because of excessive task offloading and resulting transmission congestion. Similarly, the PO scheme performs suboptimally since its fixed offloading ratio fails to adapt to the varying characteristics of different tasks. Interestingly, the EB scheme achieves the second best performance in scenario S2, as its balanced distribution of communication bandwidth among UAVs proves effective under high task density conditions. Notably, the HA algorithm maintains strong performance in scenario S2 by efficiently assigning repeated visits to nearby UAVs while avoiding conflicts. Its rapid convergence and low computational complexity make it particularly well suited for large scale scenarios dominated by high resilience level tasks and requiring real time responsiveness. The current simulation study mainly evaluates the effect of resilience-aware repeated visits on task completion time. We do not explicitly simulate UAV failures, link interruptions, or task-execution failures, in order to isolate the impact of repeated-visit scheduling. These failure scenarios can be incorporated through UAV-availability states, link-outage events, or task-success probabilities in future extensions.

VI. CONCLUSION

In this paper, we build a cooperative multi-UAV task offloading and routing framework, called TARO. By jointly optimizing task assignment, offloading decisions, and bandwidth allocation, TARO achieves efficient collaboration among heterogeneous UAVs. The proposed framework effectively minimizes the overall mission completion time while ensuring fairness and resilience across mission environments. Simulation results demonstrate that TARO consistently outperforms benchmark schemes in both efficiency and reliability, and the proposed heuristic algorithm provides a practical tradeoff between performance and computational complexity. Beyond performance gains, TARO highlights the importance of integrating resilience into multi-UAV MEC systems to sustain mission reliability under uncertain sensing, communication, and mobility conditions. Future work will extend the current framework by investigating distributed, energy-aware, and learning-based strategies, as well as more realistic wireless environments with probabilistic LoS/NLoS channel models, blockage effects, and fading-aware transmission design, in order to enhance the autonomy and robustness of resilience-aware multi-UAV coordination in large-scale UAV swarms.

APPENDIX A
PROOF OF THEOREM 1

For fixed UAV-TP association A and bandwidth allocation B , the offloading subproblem is

$$\begin{aligned} \mathcal{P}_4 : \min_{\lambda, \xi, \mu} \quad & \mu \\ \text{s.t.} \quad & T_k^{\text{fly}} + \sum_{i=0}^N \sum_{j=1}^N \sum_{q=1}^{Q_j} \alpha_{i,(j,q)}^k \xi_{j,k} \leq \mu \quad (47a) \\ & \xi_{j,k} \geq a_{j,k} \lambda_{j,k}, \quad \forall j, k, \quad (47b) \\ & \xi_{j,k} \geq c_{j,k} (1 - \lambda_{j,k}), \quad \forall j, k, \quad (47c) \\ & 0 \leq \lambda_{j,k} \leq 1, \quad \forall j, k. \quad (47d) \end{aligned}$$

Since T_k^{fly} is constant for fixed $\mathcal{A}$, and each variable pair $(\lambda_{j,k}, \xi_{j,k})$ only affects the data processing time associated with task V_j and UAV U_k , the optimization can be decomposed into independent scalar subproblems for all assigned UAV-TP pairs. Specifically, for any assigned pair (V_j, U_k) , we consider

$$\begin{aligned} \min_{\lambda_{j,k}, \xi_{j,k}} \quad & \xi_{j,k} \quad (48) \\ \text{s.t.} \quad & a_{j,k} \lambda_{j,k} - \xi_{j,k} \leq 0, \quad (49) \\ & c_{j,k} (1 - \lambda_{j,k}) - \xi_{j,k} \leq 0, \quad (50) \\ & -\lambda_{j,k} \leq 0, \quad \lambda_{j,k} - 1 \leq 0. \quad (51) \end{aligned}$$

This is a convex optimization problem, since the objective is linear and all constraints are affine. Therefore, the Karush–Kuhn–Tucker (KKT) conditions are necessary and sufficient for optimality.

Define the Lagrangian as

$$\begin{aligned} \mathcal{L}(\lambda_{j,k}, \xi_{j,k}, \eta_1, \eta_2, \eta_3, \eta_4) = & \xi_{j,k} + \eta_1 (a_{j,k} \lambda_{j,k} - \xi_{j,k}) \\ & + \eta_2 (c_{j,k} (1 - \lambda_{j,k}) - \xi_{j,k}) \\ & - \eta_3 \lambda_{j,k} + \eta_4 (\lambda_{j,k} - 1), \end{aligned} \quad (52)$$

where $\eta_1, \eta_2, \eta_3, \eta_4 \geq 0$ are the dual variables.

The KKT conditions are given as follows.

1) *Stationarity*:

$$\frac{\partial \mathcal{L}}{\partial \xi_{j,k}} = 1 - \eta_1 - \eta_2 = 0, \quad (53)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_{j,k}} = a_{j,k} \eta_1 - c_{j,k} \eta_2 - \eta_3 + \eta_4 = 0. \quad (54)$$

2) *Complementary slackness*:

$$\eta_1 (a_{j,k} \lambda_{j,k} - \xi_{j,k}) = 0, \quad (55)$$

$$\eta_2 (c_{j,k} (1 - \lambda_{j,k}) - \xi_{j,k}) = 0, \quad (56)$$

$$\eta_3 \lambda_{j,k} = 0, \quad (57)$$

$$\eta_4 (\lambda_{j,k} - 1) = 0. \quad (58)$$

3) *Primal feasibility*:

$$a_{j,k} \lambda_{j,k} - \xi_{j,k} \leq 0, \quad (59)$$

$$c_{j,k} (1 - \lambda_{j,k}) - \xi_{j,k} \leq 0, \quad (60)$$

$$0 \leq \lambda_{j,k} \leq 1. \quad (61)$$

4) *Dual feasibility*:

$$\eta_1, \eta_2, \eta_3, \eta_4 \geq 0. \quad (62)$$

Next, we derive results from the KKT conditions.

First, $\lambda_{j,k} = 0$ cannot be optimal. If $\lambda_{j,k} = 0$, then from the primal constraints we have $\xi_{j,k} \geq c_{j,k}$. To minimize the objective, it must hold that $\xi_{j,k} = c_{j,k}$. Then, from

$$\eta_1 (a_{j,k} \lambda_{j,k} - \xi_{j,k}) = \eta_1 (-c_{j,k}) = 0, \quad (63)$$

we obtain $\eta_1 = 0$. By the stationarity condition with respect to $\xi_{j,k}$, we have $\eta_2 = 1$. Since $\lambda_{j,k} = 0$, the complementary slackness condition gives $\eta_4 = 0$. Substituting these into the stationarity condition with respect to $\lambda_{j,k}$ yields

$$-c_{j,k} - \eta_3 = 0, \quad (64)$$

which implies $\eta_3 = -c_{j,k} < 0$, contradicting dual feasibility. Hence, $\lambda_{j,k} = 0$ is impossible.

Similarly, $\lambda_{j,k} = 1$ cannot be optimal. If $\lambda_{j,k} = 1$, then from the primal constraints we have $\xi_{j,k} \geq a_{j,k}$, and thus $\xi_{j,k} = a_{j,k}$ at optimum. Then,

$$\eta_2 (c_{j,k} (1 - \lambda_{j,k}) - \xi_{j,k}) = \eta_2 (-a_{j,k}) = 0 \quad (65)$$

gives $\eta_2 = 0$. By the stationarity condition with respect to $\xi_{j,k}$, we have $\eta_1 = 1$. Since $\lambda_{j,k} = 1$, the complementary slackness condition gives $\eta_3 = 0$. Then, the stationarity condition with respect to $\lambda_{j,k}$ becomes

$$a_{j,k} + \eta_4 = 0, \quad (66)$$

which is impossible because $a_{j,k} > 0$ and $\eta_4 \geq 0$. Hence, $\lambda_{j,k} = 1$ is also impossible.

Therefore, the optimal solution must satisfy

$$0 < \lambda_{j,k} < 1. \quad (67)$$

By complementary slackness, this implies

$$\eta_3 = \eta_4 = 0. \quad (68)$$

Then the stationarity conditions reduce to

$$\eta_1 + \eta_2 = 1, \quad (69)$$

$$a_{j,k} \eta_1 = c_{j,k} \eta_2. \quad (70)$$

Since $a_{j,k} > 0$ and $c_{j,k} > 0$, it follows that $\eta_1 > 0$ and $\eta_2 > 0$. Thus, by complementary slackness, both inequality constraints must be active at the optimum, i.e.,

$$a_{j,k} \lambda_{j,k} = \xi_{j,k}, \quad (71)$$

$$c_{j,k} (1 - \lambda_{j,k}) = \xi_{j,k}. \quad (72)$$

Equating the above two expressions yields

$$a_{j,k} \lambda_{j,k} = c_{j,k} (1 - \lambda_{j,k}), \quad (73)$$

from which we obtain

$$\lambda_{j,k}^* = \frac{c_{j,k}}{a_{j,k} + c_{j,k}}. \quad (74)$$

Theorem 1 is now proven.

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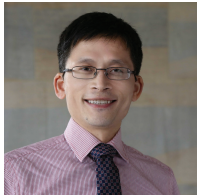


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