

Article

Task-Driven Optimization of Ground User Clustering and Channel Access in Unknown Environments: A Coalition-Based Optimal Stopping Approach

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Abstract

In emergency rescue operations, coordinating ground users (GUs) efficiently to handle dispersed tasks is crucial for saving lives and property. However, challenges such as task assignment and channel access hinder effective performance. The heterogeneity of GU abilities and the multiple ability requirements of tasks often lead to mismatched assignments, reducing rescue efficiency. Furthermore, channel access is complicated by the lack of channel state information (CSI) in disaster environments, which increases resource consumption if all channels are explored exhaustively. To address these challenges, this paper proposes a two-stage optimization framework that combines task assignment and channel access under unknown environments. First, a clustering-based method groups GUs according to multiple ability requirements. The task assignment problem is formulated as a transferable utility coalition formation game (CFG) with defined utility and preference relations. Second, a channel access mechanism is designed and modeled as an optimal stopping problem to optimize exploration time and select the optimal channel from the explored set. A task assignment and channel access optimization algorithm for cooperative rescue is proposed, where a multi-round matching preprocessing step supports coalition formation, and a one-stage look-ahead (1-SLA) rule balances exploration and data reception. Simulation results show that the proposed algorithm effectively satisfies task ability requirements, accelerates channel access, and improves the actual total utility.

Keywords: task assignment; channel access; coalition formation game; optimal stopping theory; clustering preprocess; 1-SLA rule



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1. Introduction

In emergency rescue scenarios, efficient coordination of ground users (GUs) to handle scattered tasks is key to saving lives and property. However, there are some basic challenges in the process of performing tasks, such as task assignment and channel access. For task assignment, GUs have diverse abilities, and tasks require distinct ability combinations. When task assignment is inappropriate, it may result in poor ability match between ground users and tasks, thereby diminishing the rescue efficiency. Even if the essential ability requirements of a task are not met, the task execution will fail [1]. For channel access, considering the complexity of tasks, GUs need to receive task-related data to improve the effectiveness of task execution. However, channel state information (CSI) in disaster

areas is usually unknown [2]. If the command center explores all channels first and assigns channels precisely to each task, it will consume more resources (such as time, computility, and energy) and negatively affect the execution of overall tasks. Therefore, this paper investigates task assignment and channel access problems in rescue scenarios.

There are already some existing studies that focus on task assignment and channel access problems. For task assignment, current research can be divided into ability coordination [3–6] and resource optimization [7–10]. However, multiple ability requirements of tasks are not adequately considered, and current task assignment methods cannot fully meet the multiple ability requirements of tasks. For channel access, existing research often directly assigns channels based on statistical CSI in air-ground data transmission [11–14] and pays little attention to channel access strategies under channel uncertainty in unknown environments. Although few studies consider channel uncertainty, they mostly focus on single-user scenarios [15–17], making it hard to apply them to multi-task scenarios.

To solve the above challenges, this paper focuses on task assignment and channel access optimization problems in rescue scenarios under an unknown environment. The problem is modeled as a two-stage optimization problem. First, a clustering approach is introduced to optimize collaboration among GUs, and a GU clustering optimization problem based on multiple ability requirements is proposed. This problem is modeled as a transferable utility coalition formation game (CFG), and a proper utility function and a preference relation are set to improve the execution of tasks. Then, the total channel resources are allocated to each cluster, and a channel access problem is proposed based on unknown CSI. This problem is modeled as an optimal stopping problem to optimize the exploration time and select the optimal channel from the explored channel set. Furthermore, a task assignment and channel access optimization algorithm for cooperative rescue is proposed. Specially, for task assignment, a distributed preprocessing step is added to the coalition formation scheme, and a preprocessing clustering algorithm based on multi-round matching is proposed to enhance the match between tasks and GU abilities. For channel access, a one-stage look-ahead (1-SLA) rule is considered in the channel explore to balance exploration time and data reception time.

The main conclusions of this paper are summarized as follows:

- A rescue task scenario with multiple ability requirements is considered. GUs form clusters with other GUs based on their abilities to perform tasks. Then, each cluster head accesses a channel and obtains task-related data.
- A two-stage optimization problem is proposed. Specifically, for task assignment, this problem is modeled as a transferable utility CFG, and a proper utility function and a preference relation are set to improve the execution of tasks. For channel access, this problem is modeled as an optimal stopping problem to optimize channel exploration time and select an optimal channel in the explored channel set.
- A task assignment and channel access optimization algorithm for cooperative rescue is proposed. Specifically, for task assignment, a preprocessing step is added within the distributed coalition formation scheme, and a preprocessing clustering algorithm based on multi-round matching is proposed to ensure basic coverage of ability requirements. For channel access, a 1-SLA rule is considered to balance channel exploration time and data reception time.
- Simulation results show that the proposed algorithm effectively meets task ability requirements and improves task execution. Additionally, each cluster completes channel access in a short time and enables more time to be used for task-related data reception.

Additionally, large artificial intelligence models (LAIMs) are being increasingly considered as a key component in future edge-enabled intelligent systems for autonomous decision-making in complex environments [18]. In such systems, LAIMs mainly operate

at a high-level intelligence layer to support perception, reasoning, and task generation, while their outputs still need to be executed by distributed agents under practical system constraints. In this context, the proposed task-assignment and channel-access framework provides an execution-layer support to facilitate the reliable implementation of LAIM-generated tasks in disaster-response scenarios.

2. Related Work

The earlier studies related to the current article are reviewed in this section, which is divided into two parts: (i) improvements in task assignment and (ii) optimization of channel access.

2.1. Improvements in Task Assignment

In studies related to task assignment, the authors in [3] describe UAVs collaborating to perform reconnaissance tasks by forming coalitions. Each UAV first independently selects a task to participate in. Then, it sends the collected information to the coalition head for data fusion. In [4], the authors study multi-UAVs performing monitoring tasks, which are divided into a sensing phase and a transmission phase. Compared to [3], UAVs in the sensing phase can complete multiple tasks. In [5], the authors study the cooperative multi-objective sensing tasks for large-scale moving vehicles. Vehicles perform data collection and avoid obstacles in complex environments. The authors in [6] focus on multi-target cooperative strike tasks. To better adapt to battlefield environments, different requirements are proposed for UAVs performing strike tasks based on task types. These studies explore task assignment problems with single ability requirements in depth. However, in disaster relief scenarios, tasks often involve multiple ability requirements, such as search and rescue, heavy demolition, first aid, and so on. Therefore, task assignment with multiple ability requirements should be further considered.

Additionally, apart from assigning tasks based on ability requirements, some studies currently focus on achieving efficient resource configuration from the perspective of task assignment. The authors in [7] study heterogeneous UAV networks where UAVs carry different resources. UAVs cooperate to perform multiple tasks in order of priority and form overlapping coalitions to optimize resource allocation. Building on [7], the authors in [8] further expand resource allocation to large-scale UAV scenarios. Moreover, a centralized preprocessing method is designed based on the traditional distributed coalition formation scheme to enhance scalability in large-scale UAV scenarios. The authors in [9] propose hedonic coalition formation games to optimize task offloading decisions in LEO satellite networks, enabling efficient resource allocation. In [10], the authors considered aggregating task blocks in vehicular fog computing and proposed a method combining overlapping coalition formation and matching algorithms to optimize resource allocation, leading to a noticeable reduction in latency. These studies focus on allowing one user to join multiple tasks to maximize resource utilization. However, since rescue scenarios are often time-sensitive, each GU should join only one task. Therefore, current GU cooperation methods cannot fully meet the requirements of multiple ability task scenarios.

2.2. Optimization of Channel Access

In studies related to channel access, the authors in [11] consider the coupling between channel access and power strategies in large-scale UAV networks, and a hierarchical game framework is proposed to jointly optimize both aspects. In [12], the authors examine the joint optimization of UAV deployment and user association, aiming to maximize the total system achievable rate. In [13], the authors study the joint optimization of UAV deployment and GU clustering in air-ground networks, aiming to reduce communication overhead

while ensuring the number of served GUs. The authors in [14] jointly optimize wake-up scheduling of sensor nodes and UAV trajectories to minimize the maximum energy consumption of all sensor nodes and ensure reliable data collection. These studies adopt joint optimization to adjust UAV strategies and ensure reliable data transmission, and air-ground channels are often modeled based on statistical characteristics in data transmission analysis. However, non-line-of-sight links may dominate during UAV data transmission [19], leading to strong randomness fading in air-ground channels and affecting data reception.

Under uncertain channel conditions, it is necessary to detect the CSI to identify reliable channels. The author in [15] considers the impact of time and energy consumption during channel exploration on data transmission throughput, which is modeled as an optimal stopping problem. Furthermore, [16,17] examines the channel exploration problem in covert communication scenarios. In [16], the authors propose different strategies for inactive and reactive wardens, and an optimal stopping theory is adopted to model the sequential exploration process. In [17], the authors study the problem of jammer selection and power control in multi-jammer aided covert communication. Considering the cost of acquiring CSI, an optimal stopping problem is adopted to represent the sequential exploration of jammers. These studies adopt optimal stopping theory to consider the trade-off between channel exploration cost and throughput. However, most existing research on channel exploration focuses on single-user scenarios and cannot be directly applied to multi-task scenarios. Therefore, the problem of multi-task information transmission in unknown environments should be further considered.

Note that the channel access problem based on the optimal stopping theory in the multi-task scenario considered shares certain similarities with [15]. It is necessary to further clarify the differences between the two papers. From the application perspective, this paper introduces optimal stopping theory into channel access for multi-task information transmission and integrates the stopping decision with task requirements. As a result, the system may select a channel that satisfies task requirements before the theoretically optimal stopping threshold is reached, thereby further improving overall system performance. From a technical perspective, ref. [15] normalizes large-scale fading and noise power during modeling and incorporates the energy consumption of both channel exploration and information transmission into the optimal stopping decision. In contrast, this paper explicitly retains physical system parameters such as large-scale fading and noise power in the analysis, making the results more physically interpretable. Moreover, this paper intentionally ignores energy consumption and focuses on the impact of channel quality itself on the optimal stopping decision, thereby demonstrating the applicability of optimal stopping theory to more general channel access problems.

3. System Model

As shown in Figure 1, there are N GUs and J tasks in the rescue scenario, represented by $\mathcal{N} = \{1, 2, \dots, N\}$ and $\mathcal{J} = \{1, 2, \dots, J\}$, respectively. GUs are required to participate in rescue tasks. To better meet task requirements, GUs involved in the same task form clusters to enhance collaboration. Moreover, before the tasks commence, UAVs from the command center send task-related data to each cluster head to improve the effectiveness of task execution.

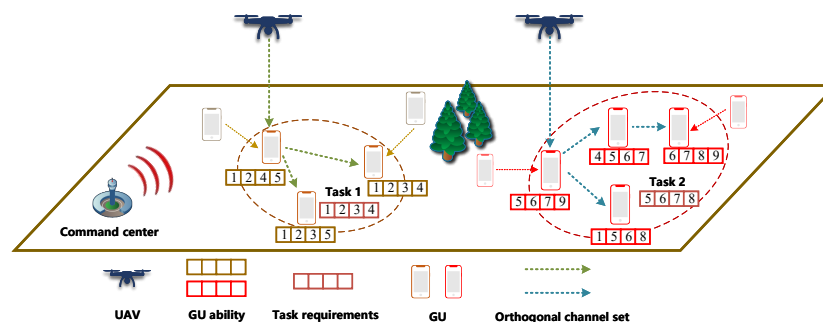


Figure 1. System model under the rescue scenario.

3.1. Ground User Collaboration Model

The collaboration relationship among GUs is influenced by both task requirements and GU abilities. Regarding the requirement characteristics of tasks, there are K types of ability requirements, represented by $\mathcal{K} = \{1, 2, \dots, K\}$. For any task j , the ability requirements form a vector $\mathcal{TA}_j = \{TA_j^1, TA_j^2, \dots, TA_j^K\}$. To measure the contribution of each ability to task j , the ability weights are denoted as $WA_j^k \in [0, 1]$. $WA_j^k = 0$ indicates that ability k is not required, and $\sum_{k \in \mathcal{K}} WA_j^k = 1$ is satisfied for any task. The set of abilities required by task j is $\mathcal{K}_j$. Furthermore, the total value of task j is $val(\mathcal{TA}_j)$, and the value of the k -th ability is defined as

$$val(TA_j^k) = WA_j^k \cdot val(\mathcal{TA}_j), \quad (1)$$

Regarding the ability features of GUs, GUs sent by the command center have abilities that can complete all tasks. For any GU n , the abilities are given by a vector $\mathcal{DA}_n = \{DA_n^1, DA_n^2, \dots, DA_n^K\}$, where $DA_n^k \in [0, 1]$ indicates the degree that GU n can independently satisfy ability k . Inspired by [3], this paper adopts a probability model to represent the degree of ability mastery. Specifically, the stronger a GU masters an ability, the higher the probability of independently satisfying this ability. For a given task, when multiple GUs support the same ability, the overall probability that the ability is fulfilled further increases. The probability that ability k in task j is expressed as [4]

$$P(TA_j^k) = 1 - \prod_{n \in CO_j} (1 - DA_n^k), \quad (2)$$

where CO_j denotes the set of GUs supporting task j . Furthermore, considering that task profit depends on the value of each ability and the probability that each ability is satisfied, the expected profit of completing task j is expressed as

$$U_j = I_j \cdot \sum_{k \in \mathcal{K}} val(TA_j^k) P(TA_j^k), \quad (3)$$

where I_j is an indicator function. From the perspective of ensuring task completeness, the indicator function is expressed as

$$I_j = \begin{cases} 1 & \text{if } \forall k \in \mathcal{K}_j, \exists n \in CO_j, DA_n^k > 0 \\ 0 & \text{otherwise,} \end{cases} \quad (4)$$

only when at least one GU supports each required ability does the task have a non-zero expected profit.

Additionally, considering GUs who meet task requirements might be outside the task area, the cost caused by movement distance should be considered. Assuming that a GU needs to move to the task center point, the movement cost for GU n to complete the task is

expressed as $Dis(n)d_{n,j}$, where $Dis(n)$ is the cost per meter for GU n , and $d_{n,j}$ is the distance between GU n and task j .

3.2. Data Transmission Model

To ensure each cluster obtains required data within limited time, the command center assigns one UAV for data transmission to each task area. The set of UAVs is denoted as $\mathcal{M} = \{m_1, m_2, \dots, m_J\}$. Data requirements are divided by ability dimension. Specifically, for any task j , the required data amount in ability k is $l_{j,k}$, and the total data requirement for task j is $l_j = \sum_{k \in \mathcal{K}} l_{j,k}$. To avoid repeated downloads, each cluster head receives data from the UAV and then distributes it to cluster members, and the set of cluster heads is denoted as $\mathcal{N}_j = \{n_1, n_2, \dots, n_J\}$. Since members stay close to the cluster head, the transmission time from the UAV to the cluster head is much longer than forwarding within the cluster. Therefore, this paper focuses on channel selection between UAVs and cluster heads.

Considering complex terrain in disaster scenarios, non-line-of-sight is dominated during air-to-ground data transmission [20], and Rayleigh fading is adopted to model small-scale fading. To reduce the control burden of the command center, it assigns channels roughly and distributes them evenly to each cluster, and each cluster head chooses the exact channel for transmission by itself. The available channel set for the cluster corresponding to task j is $\mathcal{Q}_j = \{1, 2, \dots, Q_j\}$. To prevent spectrum interference between clusters, the channel sets assigned to different clusters do not share any channels.

The available channel set of each cluster is subjected to detailed modeling. Each channel follows a block fading model; i.e., it stays constant during time T . Each cluster head spends time T_s to explore one channel. When a suitable channel is determined, the remaining time is for data transmission. Assume that the channel fading environments are homogeneous, and the channel gains are independent and identically distributed (i.i.d.). For any task j , the large-scale fading factor $1/\lambda_j$ depends on the distance between UAV m_j and the cluster head n_j . Specifically, the factor is expressed as $1/\lambda_j = d_{m_j, n_j}^{-\alpha_0}$. α_0 is the path loss exponent, which can be approximately obtained through coarse pre-deployment surveys prior to task assignment. Furthermore, for any k_j -th channel in the available channel set $\mathcal{Q}_j$, the probability density function of the channel gain η_{k_j} is expressed as [16]:

$$f_{\eta_{k_j}}(x) = \lambda_j \exp(-\lambda_j x). \quad (5)$$

If the k_j -th channel is adopted for data transmission, the data transmission rate from UAV m_j to cluster head n_j is expressed as

$$R_{k_j} = B \log_2 \left(1 + \frac{p_{m_j} \eta_{k_j}}{\sigma^2} \right), \quad (6)$$

where B is the bandwidth of channels, p_{m_j} is the transmit power of UAV m_j , and σ^2 is the additive white Gaussian noise.

3.3. Problem Formulation

To accomplish the tasks more effectively, on the one hand, it is necessary to ensure that the basic capability requirements of all tasks are satisfied, and the matching between GU abilities and task requirements is as close as possible. On the other hand, since each cluster head has no prior knowledge of the channel quality of the available channel set, it first determines its channel exploration strategy and then selects the best channel among the explored channels for data reception. Therefore, the actual utility function of task j can be designed as

$$\Theta_j = \sum_{n \in CO_j} (U_j - Dis(n)d_{n,j}) \left(\alpha \cdot \min \left(1, \frac{(T - q_j T_s) R_{q_j^{choice}}}{l_j} \right) \right). \quad (7)$$

where q_j is the number of channels explored by the cluster for task j , q_j^{choice} is the best channel among the q_j explored channels, and α is the impact of data reception on task utility. Consider that the tasks supported by each GU are determined by its clustering strategy, and the channel accessed by each cluster head is determined by the channel exploration strategy. The two strategies are denoted by $\mathcal{C} = (c_1, c_2, \dots, c_N)$ and $\mathcal{Q} = (q_1, q_2, \dots, q_j)$, respectively. Furthermore, by jointly optimizing the clustering strategy of each GU and the channel exploration strategy of each cluster head, the actual total utility will be maximized. The optimization problem is expressed as

$$\begin{aligned} & \max_{\{c_n\}_{n \in \mathcal{N}}, \{q_j\}_{j \in \mathcal{J}}} \sum_{j \in \mathcal{J}} \Theta_j(\mathcal{C}, \mathcal{Q}) \\ & s.t. \quad q_j T_s < T, \quad \forall j \in \mathcal{J} \end{aligned} \quad (8)$$

where the constraint ensures that the channel exploration time of the cluster head is less than the block fading duration, thereby reserving some time for data reception.

To maximize the actual total utility, the clustering strategies of GUs and the channel exploration strategies of all cluster heads need to be solved. Two problems should be further considered. First, clustering strategies have a large combination space and it is hard to obtain stable coalition partition. Moreover, the stable coalition partition should meet basic task ability requirements. Second, each cluster head explores more channels to improve channel quality, but the data transmission time is correspondingly reduced. Additionally, data transmission completeness directly affects the actual effectiveness of tasks. Therefore, a proper exploration strategy is needed to balance rate improvement and time cost.

4. A Two-Stage Optimization Problem Framework

Based on the problem features, this paper breaks the global optimization problem into two stages, as shown in Figure 2. In Stage I, the clustering strategies of GUs are optimized to assign GUs to the tasks that best match their abilities, which maximizes the expected total utility of all clusters. This expected total utility serves as an upper bound on the system performance. In Stage II, a channel exploration strategy is designed for each cluster head by balancing channel exploration and data transmission, aiming to improve the actual total utility of all clusters under practical channel conditions.

4.1. Stage I: Analysis of Ground User Clustering Strategy

The problem of GU clustering can be expressed as

$$\max \sum_{j \in \mathcal{J}} \sum_{n \in CO_j} (U_j - Dis(n)d_{n,j}), \quad (9)$$

Based on Formulas (2) and (3), when the GU clustering has met the basic ability requirements of the task, adding more GUs brings less of an increase to the expected utility. Therefore, it is necessary to optimize the clustering strategies of GUs to maximize the expected total utility.

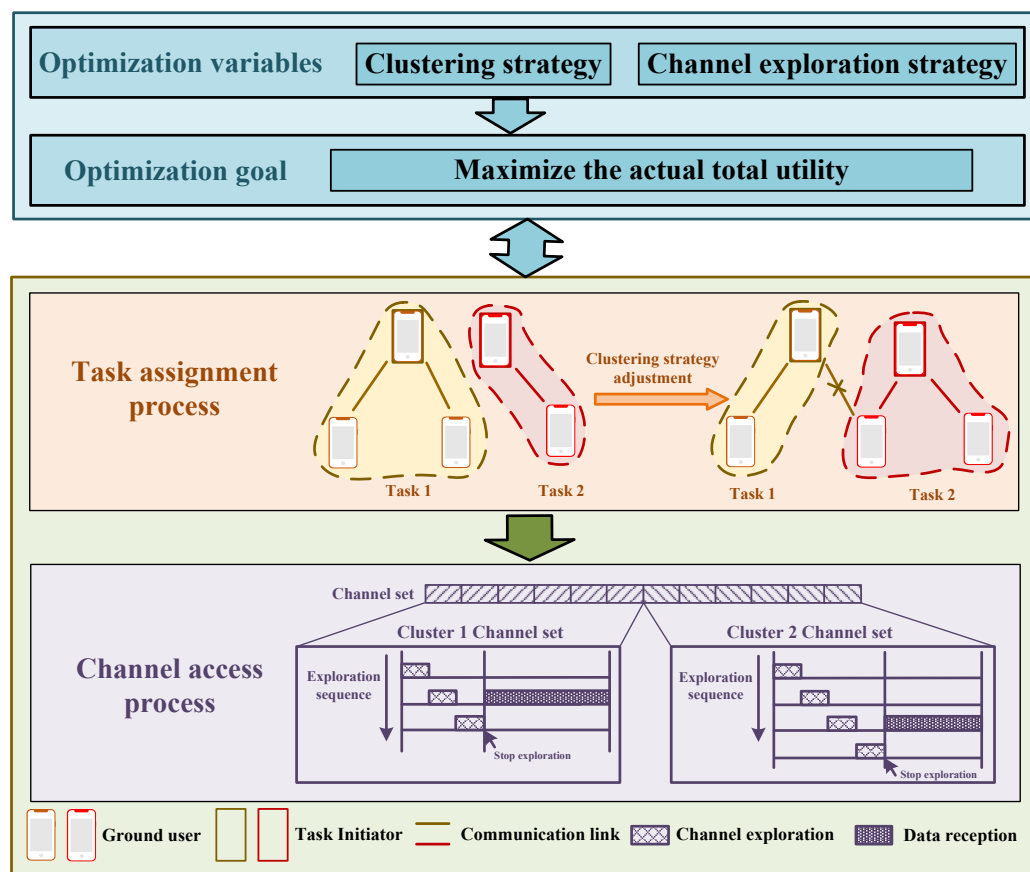


Figure 2. Illustration of the two-stage optimization framework.

The clustering strategies of GUs are modeled as a transferable utility CFG, which is expressed as $\mathcal{G} = \{\mathcal{N}, \mathcal{J}, \{u_n\}_{n \in \mathcal{N}}, \mathcal{CO}_{\mathcal{J}}, E, \{\mathcal{K}_j\}_{j \in \mathcal{J}}\}$. $\mathcal{N}$ is the set of GUs. $\mathcal{J}$ is the set of clustering strategies for the GUs. Since GUs performing the same task are considered to belong to the same cluster, the strategy set for GUs equals the task set. $\{u_n\}_{n \in \mathcal{N}}$ is the game utility function of GU n . $\mathcal{CO}_{\mathcal{J}}$ is the clustering set, which is expressed as $\mathcal{CO}_{\mathcal{J}} = \{CO_1, CO_2, \dots, CO_J\}$. E is the network topology. $\mathcal{K}_j$ is the set containing all ability requirements of task j . “Coalition” refers to “Cluster” in the following description. In a transferable utility CFG, members within the same coalition can share the total value of the coalition according to certain rules. Assuming that coalition CO_j can meet all the basic ability requirements of task j , based on the analysis in Section 3.1, the expected profit obtained by GUs in the coalition CO_j is expressed as

$$v_p(CO_j) = \sum_{k \in \mathcal{K}} val(TA_j^k) \cdot \left[1 - \prod_{n \in CO_j} (1 - DA_n^k) \right]. \quad (10)$$

Additionally, the movement cost incurred by members of coalition CO_j for completing task j is expressed as

$$v_c(CO_j) = \sum_{n \in CO_j} Dis(n) d_{n,j}. \quad (11)$$

The total value of coalition CO_j is defined as

$$v(CO_j) = v_p(CO_j) - v_c(CO_j). \quad (12)$$

During the execution of task j , each member in coalition CO_j plays an important role, and the value of each member in coalition CO_j is considered equal. Therefore, the total

value of the coalition is equally divided among its members. The utility function of each member in the coalition CO_j is expressed as

$$v_n(CO_j) = \frac{v(CO_j)}{|CO_j|}, n \in CO_j. \quad (13)$$

From the game theory perspective, changing the strategy of a GU often leads to a higher individual utility and helps the system toward a stable solution. However, in the rescue scenario, the expected utility of a task is closely related to the abilities of each GU participating in the task. A higher degree of matching between GUs' abilities and task requirements leads to a higher expected task utility and a higher utility allocated to each GU in the task. Therefore, a preference order is required to promote each GU to select a task that best match its abilities. Inspired by [21], a new preference order is introduced as follows.

Definition 1 (Coalition Order). For each GU n and $\forall CO_i, CO_j \in \mathcal{CO}_J$, if GU n prefers to join coalition CO_i , the following relationship should be satisfied:

$$\begin{aligned} CO_i \succ_n CO_j &\Leftrightarrow \sum_{m \in CO_i} u_m(CO_i) - \sum_{m \in CO_i \setminus n} u_m(CO_i \setminus n) \\ &> \sum_{m \in CO_j} u_m(CO_j) - \sum_{m \in CO_j \setminus n} u_m(CO_j \setminus n). \end{aligned} \quad (14)$$

Furthermore, if GU n is in coalition CO_j , the game utility is expressed as

$$u_n(c_n, c_{-n}) = \sum_{m \in CO_j} u_m(CO_j) - \sum_{m \in CO_j \setminus n} u_m(CO_j \setminus n), \quad (15)$$

where c_n is the coalition strategy for GU n , i.e., GU n belongs to coalition CO_j . c_{-n} is the set of coalition strategies of all GUs except GU n . The optimization goal of game $\mathcal{G}$ is expressed as

$$\underset{n \in N}{\text{maximize}} \quad u_n(c_n, c_{-n}). \quad (16)$$

To prove the existence of a stable coalition partition in the game $\mathcal{G}$, the following definitions are introduced as follows.

Definition 2 (Stable Coalition Partition [3]). A coalition strategy set $c^* = (c_1^*, c_2^*, \dots, c_N^*)$ corresponds to a stable coalition partition if and only if no GUs can improve their utility by changing their coalition strategy, which is expressed as

$$u_n(c_n^*, c_{-n}^*) \geq u_n(c_n, c_{-n}^*), \forall n \in \mathcal{N}, c_n \neq c_n^*. \quad (17)$$

Note that the definitions of stable coalition partition and Nash equilibrium (NE) are equivalent. If a coalition strategy set is proven to be an NE, then the corresponding coalition partition is stable.

Definition 3 (Exact Potential Game [22]). For a game $\mathcal{G}$, if it is an exact potential game, there exists a potential function ϕ that satisfies

$$u_n(\bar{c}_n, c_{-n}) - u_n(c_n, c_{-n}) = \phi(\bar{c}_n, c_{-n}) - \phi(c_n, c_{-n}), \forall n \in \mathcal{N}, \bar{c}_n \in \mathcal{J}, c_n \in \mathcal{J}. \quad (18)$$

According to the nature of EPG, when the game $\mathcal{G}$ is an EPG, it has at least one NE, and this shows that there is at least one stable coalition partition. The proof of the stable coalition partition is as follows.

Theorem 1. With the preference relation of coalition order, GUs take (15) as the utility function, and the transferable utility CFG $\mathcal{G}$ has at least one stable coalition partition.

Proof. The potential function is defined as the total utility of all GUs.

$$\phi(c_n, c_{-n}) = \sum_{n \in \mathcal{N}} u_n(c_n, c_{-n}). \quad (19)$$

When GU n unilaterally changes the strategy from c_n to $\bar{c}_n$, i.e., leaving coalition CO_j and joining coalition CO_i , the change in the potential function ϕ is shown as follows.

$$\begin{aligned} \phi(\bar{c}_n, c_{-n}) - \phi(c_n, c_{-n}) &= \sum_{n \in \mathcal{N}} u_n(\bar{c}_n, c_{-n}) - \sum_{n \in \mathcal{N}} u_n(c_n, c_{-n}) \\ &= \sum_{m \in CO_i} u_m(CO_i) + \sum_{m \in CO_j \setminus n} u_m(CO_j \setminus n) + \sum_{m \in \text{others}} u_m(\bar{c}_n, c_{-n}) \\ &\quad - \left[\sum_{m \in CO_i \setminus n} u_m(CO_i \setminus n) + \sum_{m \in CO_j} u_m(CO_j) + \sum_{m \in \text{others}} u_m(c_n, c_{-n}) \right] \\ &= \sum_{m \in CO_i} u_m(CO_i) - \sum_{m \in CO_i \setminus n} u_m(CO_i \setminus n) - \left[\sum_{m \in CO_j} u_m(CO_j) - \sum_{m \in CO_j \setminus n} u_m(CO_j \setminus n) \right] \\ &= u_n(\bar{c}_n, c_{-n}) - u_n(c_n, c_{-n}), \end{aligned} \quad (20)$$

where $u_m(\bar{c}_n, c_{-n})$ and $u_m(c_n, c_{-n})$ are the total utility of GUs in other coalitions except CO_i and CO_j . Since the change of coalition strategy by GU n does not affect these GUs, the two terms are equal.

According to formula (20), when GU n unilaterally changes the coalition strategy, the change in game utility function equals the change in the potential function. Therefore, the transferable utility CFG $\mathcal{G}$ is an EPG and has at least one NE. Furthermore, the coalition structure of the GUs has at least one stable coalition partition. $\square$

4.2. Stage II: Analysis of Channel Exploration Strategy

After the clustering strategy set of GUs $c^* = (c_1^*, c_2^*, \dots, c_N^*)$ is determined, the channel exploration strategy is further optimized. The channel exploration problem is modeled as

$$\begin{aligned} \max \sum_{j \in \mathcal{J}} EU_j \cdot \left(\alpha \cdot \min \left(1, \frac{(T - q_j T_s) R_{q_j^{\text{choice}}}}{l_j} \right) \right), \\ \text{s.t. } Q_j T_s < T, \forall j \in \mathcal{J} \end{aligned} \quad (21)$$

where EU_j is the expected utility of task j under the current clustering strategy set of GUs. Since the expected utility of each cluster does not depend on the channel exploration strategy, it can be treated as a constant in Stage II. Moreover, the data reception completeness of each cluster head only depends on the accessed channel gain and the transmission time and has nothing to do with the clustering strategy of each GU. This section decouples the data reception problem from the expected clustering utility and optimizes the channel access strategy to improve data reception completeness.

Considering all channels in the scenario are mutually orthogonal and the channel subsets assigned to different clusters do not overlap, the channel access of different clusters does not interfere with each other. Consequently, the channel access process of each cluster can be regarded as an independent event. For any task j , the channel exploration problem can be reformulated as a data reception ratio problem, which is expressed as

$$v_{q_j}(\eta_{q_j}^{\max}) = \frac{T - q_j T_s}{l_j} \cdot c \ln(1 + b \eta_{q_j}^{\max}), \quad (22)$$

where b and c are constants, which are calculated as $c = B/\ln 2$ and $b = p_{m_j}/\sigma^2$, respectively. $\eta_{q_j}^{\max}$ is the maximum channel gain among the explored channels q_j , which is calculated as $\eta_{q_j}^{\max} = \max_{1 \leq k_j \leq q_j} \{\eta_{k_j}\}$. The optimization goal is expressed as:

$$\max_{q_j \in Q_j} v_{q_j}(\eta_{q_j}^{\max}) \quad (23)$$

To achieve the optimization goal, two aspects can be considered. On one hand, explore more channels to obtain better channel gain. On the other hand, reduce the number of explored channels to increase data transmission time. However, exploring more channels improves channel gain but takes more time and reduces transmission time, and reducing the number of explored channels increases transmission time but may lead to insufficient channel gain. There is a clear conflict between the two aspects. Therefore, an appropriate stopping time needs to be determined based on the currently observed $\eta_{q_j}^{\max}$.

The optimization problem belongs to the class of optimal stopping problems. Considering the limited number of channels, the cluster head must stop channel exploration and begin data transmission within a limited number of explorations. The classic solution method for this problem is the backward induction method [23]. Specifically, it first assumes that $Q_j - 1$ channels have been explored and decides whether to stop based on the currently observed channel gain. If stopping fails, it continues by assuming $Q_j - 2, Q_j - 3 \dots$ channels have been explored until the optimal stopping time is determined. Assuming that currently q_j channels have been explored, then under this exploration, the achievable data reception ratio is expressed as

$$v_{q_j}(\eta_1, \eta_2, \dots, \eta_{q_j}) = \begin{cases} v_{q_j}(\eta_{Q_j}^{\max}), & q_j = Q_j \\ \max\{v_{q_j}(\eta_{q_j}^{\max}), E_{\eta_{q_j+1}}[v_{q_j+1}(\eta_{q_j}^{\max}, \eta_{q_j+1}) | \{\eta_{k_j}\}_{k_j=1}^{q_j}]\}, & \text{otherwise.} \end{cases} \quad (24)$$

Furthermore, the optimal stopping time obtained by the backward induction method can be expressed as

$$q_j^{opt} = \min\{1 \leq q_j \leq Q_j : v_{q_j}(\eta_{q_j}^{\max}) \geq E_{\eta_{q_j+1}}[v_{q_j+1}(\eta_{q_j}^{\max}, \eta_{q_j+1}) | \{\eta_{k_j}\}_{k_j=1}^{q_j}]\}. \quad (25)$$

It should be noted that this method has a high computational complexity. This is because when the optimal stopping time is q_j , $E_{\eta_{m_j+1}}[v_{m_j+1}(\eta_{m_j}^{\max}, \eta_{m_j+1}) | \{\eta_{k_j}\}_{k_j=1}^{m_j}]_{m_j=q_j}^{Q_j-1}$ needs to be calculated. The computation grows exponentially as the number of available channels increases, making it impractical for real applications. Therefore, a low-complexity channel exploration method needs to be designed.

4.3. Algorithm Design

In the algorithm design, a preprocessing clustering algorithm based on multi-round matching is first proposed to meet the basic ability requirements of each task, as shown in Algorithm 1. Specifically, tasks are ranked from high to low according to their value, and in each round the matching between GUs and tasks follows this sequence. During each round, each task calculates its remaining unmet ability requirements and selects a GU from the available GU set who maximally satisfies these requirements. If a GU is matched to a task, it will be removed from the available GU set. When the basic ability requirements of all tasks are met, the preprocessing completes.

Then, a task assignment and channel access optimization algorithm for cooperative rescue is proposed to obtain a stable coalition partition for GUs and the optimal channel access strategy for each cluster head, as shown in Algorithm 2. For task assignment, to prevent the ability requirements of tasks from being affected during the process of GUs

adjusting their clustering strategies, GUs outside the clusters first attempt to join tasks, followed by adjustment of GU clustering strategies among tasks. For channel access, to reduce computational complexity, inspired by [15], this paper adopts a channel exploration method based on the 1-SLA rule to achieve optimal exploration. The optimal stop time under this rule is expressed as

$$q_j^{1SLA} = \min\{1 \leq q_j \leq Q_j : v_{q_j}(\eta_{q_j}^{\max}) \geq E_{\eta_{q_j+1}}[U_{q_j+1}(\eta_{q_j}^{\max}, \eta_{q_j+1}) | \{\eta_{k_j}\}_{k_j=1}^{q_j}]\}, \quad (26)$$

where $U_{q_j+1}(\eta_{q_j}^{\max}, \eta_{q_j+1}) = v_{q_j+1}(\eta_{q_j+1}^{\max})$ is the achievable data reception ratio when the cluster head has explored q_j channels and starts transmission on the $q_j + 1$ channel.

Based on the known maximum channel gain from the current channel exploration, the expected data reception ratio for the next channel exploration is derived as follows:

$$\begin{aligned} E_{\eta_{q_j+1}}[U_{q_j+1}(\eta_{q_j}^{\max}, \eta_{q_j+1}) | \{\eta_{k_j}\}_{k_j=1}^{q_j}] &= d(q_j + 1) E_{\eta_{q_j+1}}[\ln(1 + b \max\{x, y\})] \\ &= d(q_j + 1) \lambda_j \cdot \left[\int_0^x \ln(1 + bx) e^{-\lambda_j y} dy + \int_x^\infty \ln(1 + by) e^{-\lambda_j y} dy \right] \\ &= d(q_j + 1) \left[\ln(1 + bx)(1 - e^{-\lambda_j x}) + \ln(1 + bx) e^{-\lambda_j x} + e^{\frac{\lambda_j}{b}} E_1\left(\lambda_j \cdot \frac{1 + bx}{b}\right) \right] \\ &= d(q_j + 1) \left[\ln(1 + bx) + e^{\frac{\lambda_j}{b}} E_1\left(\lambda_j \cdot \frac{1 + bx}{b}\right) \right], \end{aligned} \quad (27)$$

where $d(q_j + 1) = \frac{T - (q_j + 1)T_s}{l_j} \cdot c$, $x = \eta_{q_j}^{\max}$, $y = \eta_{q_j+1}$. $E_1(z)$ is the exponential integral function, which is defined as $E_1(z) = \int_z^\infty \frac{e^{-t}}{t} dt$.

Algorithm 1 Preprocessing clustering algorithm based on multi-round matching

Input: For $\forall j \in \mathcal{J}$, the ability requirements vector $\mathcal{TA}_j$, the task value $val(\mathcal{TA}_j)$. For $\forall n \in \mathcal{N}$, the ability vector $\mathcal{DA}_n$. The network topology E . The free GU set $\mathcal{F}$.

Output: The initial coalition partition set $CO_{\mathcal{J}}$.

While: There exist tasks that have basic ability requirements remaining unmet.

1) Generate sequence $\mathcal{W}$ by ranking tasks with unmet basic abilities from highest to lowest value.

Loop: For task $w = 1 : 1 : \mathcal{W}$

2) Determine the unmet ability requirements $\mathcal{TA}_{j_unmet}$ for task w .

3) Select GU n from set $\mathcal{F}$ who satisfies the greatest number of ability requirements $\mathcal{TA}_{j_unmet}$. If multiple GUs satisfy the same number, choose the one closest to task w .

4) Add GU n to set CO_w and remove it from set $\mathcal{F}$.

End loop

End While

Theorem 2. The proposed task assignment and channel access optimization algorithm for cooperative rescue can converge to a stable solution.

Proof. During the coalition formation process, the number of tasks is equal to the number of coalitions, and the number of GUs is finite. Therefore, the total number of possible coalition partitions is finite. In each iteration, a change in the clustering strategy is allowed only if it strictly improves the game utility of the GU. According to (19), the potential function is defined as the sum of the utilities of all GUs, i.e., the expected total utility. Furthermore, Theorem 1 shows that any increase in an individual GU's game utility leads to a corresponding increase in the expected total utility. Since the expected total utility is upper bounded and the number of possible coalition partitions is finite, the coalition formation process cannot continue indefinitely and must terminate within a finite number of steps. As a result, a stable coalition partition is obtained at the end of the coalition formation

process, where no GU can further improve its game utility by changing its clustering strategy. During the channel access process, each cluster head selects one transmission channel from a finite set of available channels. Because the number of available channels is limited, the channel exploration process is guaranteed to terminate. After exploration, each cluster head chooses the channel with the best quality from the explored set, which corresponds to a stable channel access strategy. In summary, the proposed task assignment and channel access optimization algorithm converges to a stable solution within a finite number of iterations. $\square$

Algorithm 2 Task assignment and channel access optimization algorithm for cooperative rescue

Input: For $\forall j \in \mathcal{J}$, the ability requirements vector $\mathcal{TA}_j$, the task value $val(\mathcal{TA}_j)$, the available channel set for cluster head $\mathcal{Q}_j$, the data requirement l_j . For $\forall n \in \mathcal{N}$, the ability vector $\mathcal{DA}_n$. The network topology E . The initial coalition partition $CO_{\mathcal{J}}$ in Algorithm 1. The exploration time T_s . The total time T . The maximum iteration I_{max} .

Output: The coalition partition set $CO_{\mathcal{J}}$. The channel access strategy set $\eta_{q_{\mathcal{J}}}^{max}$.

Stage I: Coalition Formation Algorithm

- 1) Randomly sequence $\mathcal{W}$, prioritizing GUs outside $CO_{\mathcal{J}}$ before those inside.
- 2) Select GU n based on sequence $\mathcal{W}$, then try to join other GU clusters and calculate the game utility $u_n(CO) = \{u_n(CO_1), u_n(CO_2), \dots, u_n(CO_J)\}$. If a higher game utility exists, the GU joins that cluster and updates $CO_{\mathcal{J}}$.
- 3) Repeat step 1 and step 2 until I_{max} is reached.

Stage II: Optimal Stopping Algorithm

- 1) Each cluster in $CO_{\mathcal{J}}$ elects a cluster head n_j , and sets the exploration count $q_j = 1$.
 - 2) Each cluster head n_j determines the channel gain $\eta_{q_j}^{max}$ in the current exploration channel set, and calculates $E_{\eta_{q_j+1}}[U_{q_j+1}(\eta_{q_j}^{max}, \eta_{q_j+1}) | \{\eta_{k_j}\}_{k_j=1}^{q_j}]$ by Formula (27).
 - 3) Determine whether $v_{q_j}(\eta_{q_j}^{max}) \geq 1$ or $v_{q_j}(\eta_{q_j}^{max}) \geq E_{\eta_{q_j+1}}[U_{q_j+1}(\eta_{q_j}^{max}, \eta_{q_j+1}) | \{\eta_{k_j}\}_{k_j=1}^{q_j}]$ holds based on Formulas (22) and (26). If the condition is satisfied output $\eta_{q_j}^{max}$, otherwise $q_j = q_j + 1$.
 - 4) Repeat step 2 and step 3 until all clusters determine $\eta_{q_j}^{max}$.
-

Furthermore, the optimality of the 1-SLA rule will be proved for the channel exploration problem in the considered data transmission scenario.

Definition 4 (Monotonicity Event). $v_{q_j}(\eta_{q_j}^{max}) \geq E_{\eta_{q_j+1}}[U_{q_j+1}(\eta_{q_j}^{max}, \eta_{q_j+1}) | \{\eta_{k_j}\}_{k_j=1}^{q_j}]$ is denoted as event A_{q_j} . If the event satisfies the following relationship, the stopping problem is regarded as monotone.

$$A_1 \subset A_2 \subset \dots \subset A_{Q_j}. \quad (28)$$

Lemma 1. In a finite horizon monotone stopping rule problem, the 1-SLA rule is optimal [23].

Theorem 3. In the considered data transmission scenario, the 1-SLA rule is optimal and maximizes the expected data reception ratio.

Proof. In the considered data transmission scenario, the finite-dimension property holds naturally. Therefore, the monotonicity problem will be analyzed based on the 1-SLA rule. The following function is defined as

$$\begin{aligned} F_{q_j}(\eta_{q_j}^{max}) &= v_{q_j}(\eta_{q_j}^{max}) - E_{\eta_{q_j+1}}[U_{q_j+1}(\eta_{q_j}^{max}, \eta_{q_j+1}) | \{\eta_{k_j}\}_{k_j=1}^{q_j}] \\ &= G_{q_j}(\eta_{q_j}^{max}) - H_{q_j}(\eta_{q_j}^{max}), \end{aligned} \quad (29)$$

where

$$\begin{cases} G_{q_j}(\eta_{q_j}^{\max}) = [d(q_j) - d(q_j + 1)] \ln(1 + b\eta_{q_j}^{\max}) \\ H_{q_j}(\eta_{q_j}^{\max}) = d(q_j + 1)e^{\frac{\lambda_j}{b}} E_1\left(\lambda_j \cdot \frac{1 + b\eta_{q_j}^{\max}}{b}\right) \end{cases} \quad (30)$$

The monotonicity of $G_{q_j}(\eta_{q_j}^{\max})$ and $H_{q_j}(\eta_{q_j}^{\max})$ is further analyzed. As $\eta_{q_j}^{\max}$ increases, $G_{q_j}(\eta_{q_j}^{\max})$ strictly increases, and $H_{q_j}(\eta_{q_j}^{\max})$ strictly decreases. Additionally, by analyzing the monotonicity of $d(q_j)$, the following relationships can be obtained:

$$\begin{cases} d(q_j) > d(q_j + 1) \\ d(q_j) - d(q_j + 1) = d(q_j + 1) - d(q_j + 2) \end{cases} \quad (31)$$

Comparing $F_{q_j}(\eta_{q_j}^{\max})$ and $F_{q_j+1}(\eta_{q_j+1}^{\max})$, the following expression is derived:

$$F_{q_j+1}(\eta_{q_j+1}^{\max}) - F_{q_j}(\eta_{q_j}^{\max}) = G_{q_j+1}(\eta_{q_j+1}^{\max}) - G_{q_j}(\eta_{q_j}^{\max}) + H_{q_j}(\eta_{q_j}^{\max}) - H_{q_j+1}(\eta_{q_j+1}^{\max}), \quad (32)$$

where $\eta_{q_j+1}^{\max} = \max\{\eta_{q_j+1}, \eta_{q_j}^{\max}\} \geq \eta_{q_j}^{\max}$.

Based on the above monotonicity analysis, the following relationships can be obtained:

$$\begin{cases} G_{q_j+1}(\eta_{q_j+1}^{\max}) \geq G_{q_j}(\eta_{q_j}^{\max}) \\ H_{q_j}(\eta_{q_j}^{\max}) > H_{q_j+1}(\eta_{q_j+1}^{\max}) \geq H_{q_j+1}(\eta_{q_j+1}^{\max}). \end{cases} \quad (33)$$

According to Formulas (32) and (33), it can be concluded that $F_{q_j+1}(\eta_{q_j+1}^{\max}) > F_{q_j}(\eta_{q_j}^{\max})$. Furthermore, if $F_{q_j}(\eta_{q_j}^{\max}) > 0$, then $F_{q_j+1}(\eta_{q_j+1}^{\max}) > 0$, and the event $A_{q_j} \subset A_{q_j+1}$. Therefore, the optimal stopping problem in the considered data transmission scenario is monotone, and the 1-SLA rule is optimal. $\square$

Based on the good properties of the 1-SLA rule, the optimal stopping problem can be further simplified. The following proposition is established.

Proposition 1. *In the considered data transmission scenario, the optimal stopping problem in Equation (26) can be transformed into a threshold rule based on channel gain, which is expressed as*

$$q_j^{thr} = \min\{1 \leq q_j \leq Q_j : \eta_{q_j}^{\max} > a_j\}, \quad (34)$$

where the threshold value a_j is satisfied as $F_{q_j}(a_j) = 0$.

Proof. Based on the monotonicity proof of $F_{q_j}(\eta_{q_j}^{\max})$ in Theorem 2, the existence of its zero point is further proven. The following equations hold:

$$\begin{cases} F_{q_j}(0) = -d(q_j + 1)e^{\frac{\lambda_j}{b}} E_1\left(\lambda_j \cdot \frac{1}{b}\right) \\ \lim_{\eta_{q_j}^{\max} \rightarrow \infty} F_{q_j}(\eta_{q_j}^{\max}) = [d(q_j) - d(q_j + 1)] \ln(1 + b\eta_{q_j}^{\max}) \end{cases} \quad (35)$$

It is observed that $F_{q_j}(0) < 0$ and $\lim_{\eta_{q_j}^{\max} \rightarrow \infty} F_{q_j}(\eta_{q_j}^{\max}) > 0$. According to the zero point existence theorem, there is a unique solution a_j such that $F_{q_j}(a_j) = 0$. $\square$

It should be noted that although Proposition 1 does not provide a closed-form solution for the threshold, it plays an important role in further reducing computational complexity. Specifically, if the threshold can be precomputed and stored in the cluster head, the access channel can be quickly determined by comparing the observed channel gain with the threshold value.

5. Simulation and Discussion

This section verifies the effectiveness of the proposed algorithm by the simulation platform MATLAB R2018B. To avoid randomness in the experimental results, 500 scenarios are generated randomly in the simulations, and 100 independent experiments are conducted for each scenario. To better demonstrate the advantages of the proposed algorithm, several common baseline algorithms are described as follows.

- K-means clustering algorithm: Use the task location as the clustering center for GU clustering and obtain clusters corresponding to each task by the K-means algorithm.
- Full exploration algorithm: Each cluster head detects all assigned channels and then selects the optimal channel for data reception.
- Random channel access algorithm: Each cluster head randomly selects one channel from its available channel set to receive data.

5.1. Simulation Setup

There are 4 tasks and 20 GUs uniformly and randomly distributed in the $1 \text{ km} \times 1 \text{ km}$ rescue scenario. Referring to [3,15,16], the parameters are shown in Table 1, where for $\forall j \in \mathcal{J}$, the task value is $val(\mathcal{T}A_j) \in [7.5, 9.5]$, the total number of task ability requirement is $\mathcal{K} = 6$, the number of each task ability requirement is $\mathcal{K}_j = 4$, each ability data requirement is $l_{j,k} \in [130, 160] \text{ kbit}$, and the transmit power of UAV m_j is $p_{m_j} = 10 \text{ dBm}$. For $\forall n \in \mathcal{N}$, the ability master degree is $DA_n^k \in [0.4, 0.8]$, $k \in \mathcal{K}$ and the movement cost is $Dis(n) = 10^{-4}$. The total channel number is $Q = 60$. The block fading time is $T = 100 \text{ ms}$. Each channel exploration time is $T_s = 3 \text{ ms}$. The noise variance is $\sigma^2 = 0 \text{ dBm}$. The large fading channel gain is $\lambda_j = 1$, and the small-scale fading channel gain is randomly generated according to the exponential distribution defined in Formula (5). For the ability weights WA_j^k , this paper assumes that all abilities contribute equally to the same task.

Table 1. Parameter settings.

Parameter	Value	Parameter	Value
$val(\mathcal{T}A_j)$	$[7.5, 9.5]$	$\mathcal{K}$	6
$\mathcal{K}_j$	4	$l_{j,k}$	$[130, 160] \text{ kbit}$
p_{m_j}	10 dBm	DA_n^k	$[0.4, 0.8]$
$Dis(n)$	10^{-4}	Q	60
T	100 ms	T_s	3 ms
σ^2	0 dBm	λ_j	1

5.2. Analysis of Simulation

Figure 3 shows the simulation scenario diagram. The center location of each task is indicated by a red star. GUs move to task centers based on their mastered abilities and the abilities required by tasks. When the basic ability requirements of tasks are met, GUs further adjust their cluster strategies to improve the overall expected utility of tasks. Due to cost constraints caused by distance, GUs generally avoid tasks that are located far away.

Figure 4 shows the convergence curves of the coalition formation process in Stage I under different numbers of GUs and tasks. When the number of tasks stays the same, the increase in ground users causes more exploration and adjustment to find the final cluster strategies of the GUs, so the iteration count also rises. When the number of ground users stays the same, the increase in tasks has little effect on the number of iterations. It is shown that more tasks only increase the number of GU clusters and do not clearly affect the exploration of cluster strategies.

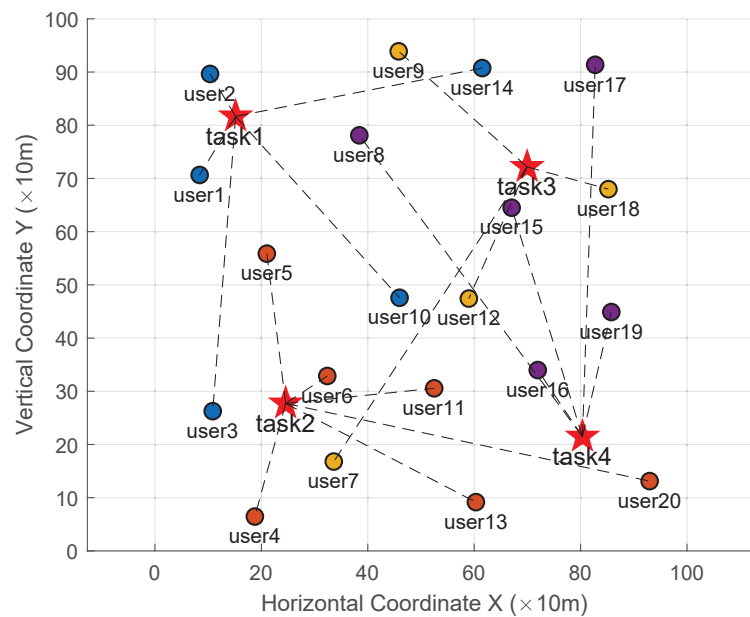


Figure 3. The simulation scenario diagram.

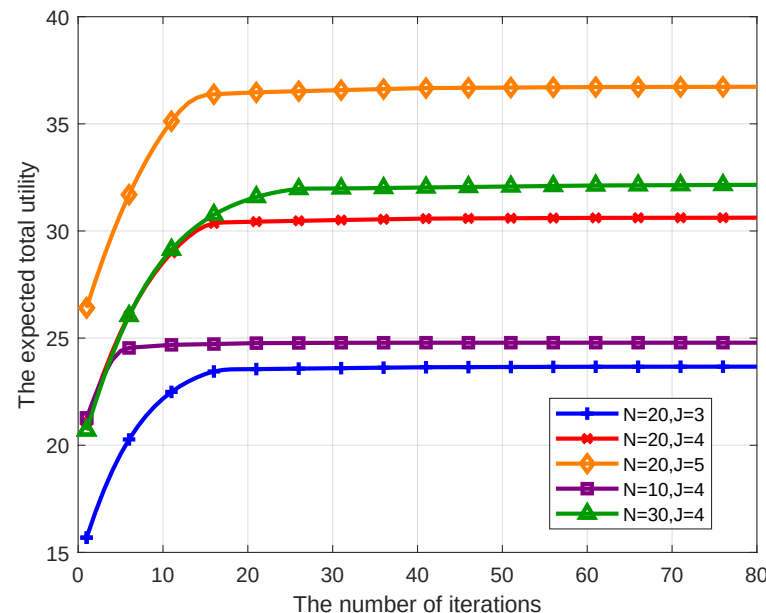


Figure 4. The convergence curves of the coalition formation process.

Figure 5 shows the number of channel explorations before stopping. Since channel resources are equally assigned to different clusters and each cluster head explores channels independently, the number of stopped explorations among clusters is averaged for analysis. As the exploration time for a single channel increases, cluster heads lose more transmission time by continuing exploration, which reduces the expected achievable data reception ratio. Therefore, cluster heads tend to stop exploration earlier and start data reception. In addition, when the total exploration time is fixed, the expected stopping channel count grows more slowly as the number of channels increases. The reason is that increasing the number of explored channels results in more transmission time being sacrificed, which leads cluster heads to prefer exploring some channels rather than all channels.

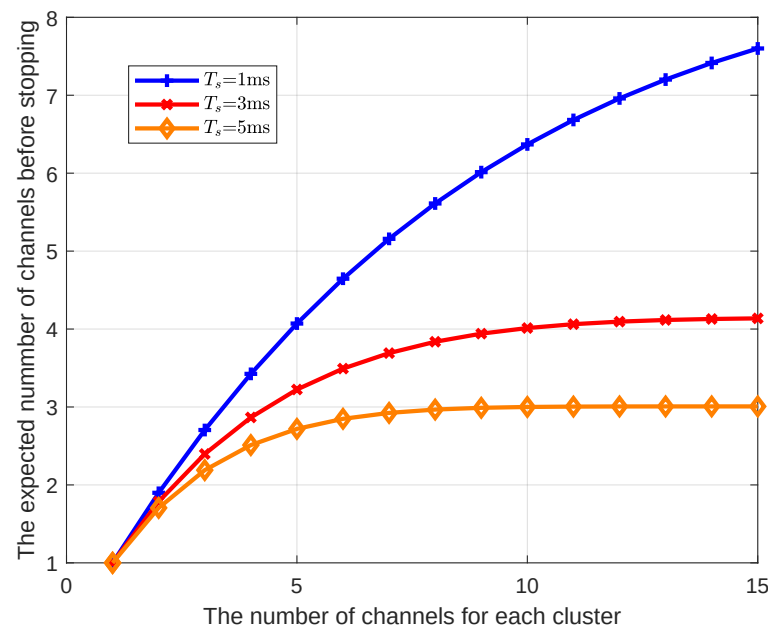


Figure 5. The number of channel explorations before stopping.

Figure 6 shows the actual total utility under different numbers of GUs. The variation in the number of ground users mainly affects the clustering performance. As the number of GUs increases, task ability requirements are satisfied more effectively and the actual total utility rises. For the coalition formation algorithm, once the basic task ability requirements are met, the actual total utility shows diminishing returns as the number of GUs keeps growing. Therefore, the total utility under the coalition formation algorithm gradually stabilizes. In contrast, the K-means clustering algorithm does not consider ability matching during clustering, resulting in performance inferior to that of the coalition formation algorithm.

Figure 7 shows the actual total utility under different numbers of tasks. For GU clustering, the actual total utility of the coalition formation algorithm increases as the number of tasks rises, which can be attributed to two main factors. First, a greater number of tasks directly leads to an increase in the expected total utility. Second, although a higher task count may reduce the number of members in each cluster, the coalition formation algorithm effectively aligns GU abilities with task requirements, resulting in an overall increase in utility. In contrast, the K-means algorithm primarily clusters GUs based on spatial distance, neglecting their abilities and task requirements. As cluster member counts decrease, the actual total utility for task completion diminishes, potentially causing some tasks to remain unfinished. Therefore, when the number of tasks exceeds four, a slight decline in utility is observed.

For channel access, more tasks correspond to fewer channels allocated to each task. For both the optimal stopping algorithm and the random channel access algorithm, data reception starts after a fixed number of channels are explored. Therefore, changes in the number of channels do not significantly affect the actual utility. Conversely, the full channel exploration algorithm benefits from fewer explored channels, allowing clusters to allocate more time for data reception. As a result, the algorithm exhibits the largest utility increase as the number of tasks increases.

Figure 8 shows the actual total utility under different numbers of task ability requirements. For GU clustering, the coalition formation algorithm consistently outperforms the K-means clustering algorithm. This is because the coalition formation algorithm matches GUs more accurately according to task ability requirements, showing better adaptability under varying ability requirements.

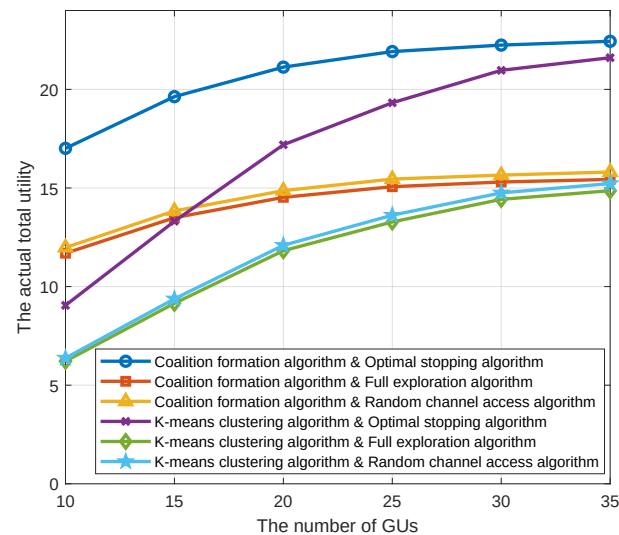


Figure 6. Actual total utility under different numbers of GUs.

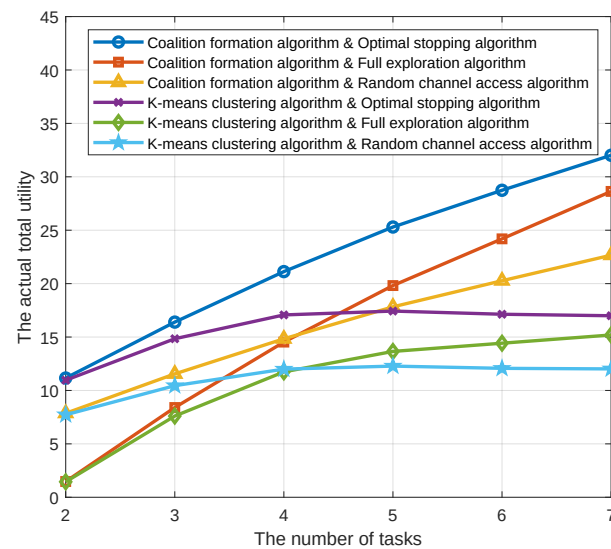


Figure 7. Actual total utility under different numbers of tasks.

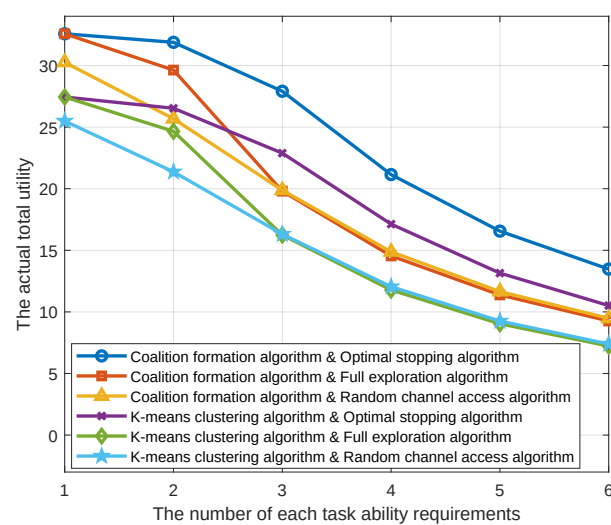


Figure 8. Actual total utility under different numbers of task ability requirements.

For channel access, when the number of ability requirements is small, the data demand within clusters is also small. Both the optimal stopping algorithm and the full exploration algorithm perform well. These methods allow cluster heads to select better channels,

resulting in a higher probability of completing full data reception. As the number of ability requirements increases, data demand within clusters also rises. The performance of the full exploration algorithm decreases significantly and approaches that of the random channel access algorithm. This is because the full exploration algorithm sacrifices a large amount of data reception time to improve channel quality, which reduces the probability of completing full data reception when data demand increases.

6. Conclusions

This paper presents a two-stage optimization framework for task assignment and channel access in emergency rescue scenarios under uncertain environments. The task assignment problem is modeled as a transferable utility coalition formation game and the channel access problem is modeled as an optimal stopping problem. A task assignment and channel access optimization algorithm for cooperative rescue is proposed to enhance ability–task matching and balance channel exploration. Simulation results confirm that the proposed algorithm improves the task execution and channel exploration strategy.

It is worth noting that the current model relies on several simplifying assumptions, such as independent and identically distributed (i.i.d.) channel conditions and static task locations during the decision horizon. In future work, the proposed framework can be extended to more dynamic scenarios by considering time-correlated channels, mobile rescue agents, and dynamically arriving tasks. Another possible extension is to relax the orthogonal-channel assumption and consider spectrum sharing with inter-cluster interference in the optimal stopping–based decision framework. Incorporating learning-based approaches and real-time adaptation mechanisms is also a promising direction to further improve system robustness and scalability in complex emergency rescue environments.

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