Adaptive UAV Mission Planning Using Ontologies and Agent Role-Based Cooperation

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Abstract

Mission planning for unmanned aerial vehicle (UAV) swarms in multi-agent systems (MAS) necessitates efficient task allocation to ensure survivability, self-organization, and successful mission completion. This paper presents a hybrid planning approach combining role-based task allocation (RBTA) and an ontology-driven methodology to formalize MAS domain knowledge. This integration reduces computational overhead, optimizes flight control execution, and enhances system autonomy. Mathematical models for RBTA are developed, incorporating key cost factors (time, energy, agent suitability) and task prioritization mechanisms, along with dynamic role reassignment strategies to address UAV failures. The proposed algorithm is formalized in a graph-based scheme comprising five core modules: role assignment, task allocation, swarm self-organization, monitoring and adaptation, and performance evaluation. Ontologies ensure semantic consistency among agents, while RBTA facilitates planning through predefined roles (leader or scout). Empirical results obtained using Python demonstrate a 15–20% reduction in mission execution time compared to conventional methods, alongside a 25% decrease in communication overhead. The proposed approach proves particularly effective in dynamic environments where rapid adaptation and fault tolerance are critical.

Keywords

multi-agent systems, UAV mission planning, task allocation, role-based task allocation, ontology, ontology-based scheduling, swarm self-organization

1. Introduction

Contemporary unmanned aerial vehicle (UAV) swarm operations span diverse applications, from critical territory monitoring to complex search and rescue missions [1, 2]. These diverse use cases impose progressively rigorous requirements on planning efficiency. The fundamental challenge lies in the dynamic allocation of resources, notably in operating under conditions characterized by incomplete information, rapidly variable external factors, and stringent temporal and energetic constraints. Traditional mission planning approaches, predominantly based on centralized control paradigms, frequently exhibit substantial limitations in flexibility, consequently impairing their adaptability to real-time environmental changes [3, 4].

Traditional task allocation methods, such as centralized planning and auction-based approaches, frequently fail to provide sufficient flexibility and operational efficiency [5, 6]. This is particularly evident in resource-constrained and rapidly changing operational environments. Given these constraints, modern planning systems increasingly integrate sophisticated algorithmic methods and systematically embed artificial intelligence techniques. Together, these approaches substantially enhance autonomy and overall operational effectiveness [3, 7, 8, 9]. The systematic integration of ontologies [2, 10, 11] with role-based task allocation (RBTA) [12] offers a promising solution. This approach excels in effectively managing complex and rapidly changing dynamic scenarios.

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Task allocation of UAV swarm requires optimal assignment of tasks among individual drones [13, 14]. This sophisticated process must account for their diverse capabilities, inherent operational constraints, and prevailing environmental dynamics. The primary objective is to maximize mission effectiveness while concurrently minimizing resource expenditure. Critical planning dimensions consequently encompass:

- resource optimization [14, 15, 16] — allocating tasks while considering execution time, energy consumption, and UAV operational characteristics
- adaptability to environmental changes [5, 8] — enabling real-time task and route adjustments in response to UAV failures, modifications in mission objectives, environmental obstacles, and weather conditions
- coordination in multi-agent systems (MAS) [2, 5, 11, 17] — facilitation of decentralized decision-making, reduction of communication overhead, and mitigation of inter-agent conflicts.

Based on these premises, our solution introduces an innovative combination of three core components within a multi-agent system architecture [2, 11]. The core components comprise:

- a multi-agent system that enables decentralized decision-making and ensures a high degree of autonomy for each UAV as well as the system as a whole
- ontological modeling offers a formalized representation of knowledge regarding the subject domain, tasks, and resources
- a hybrid RBTA algorithm, integrated with the ontological approach, facilitates efficient task distribution among agents based on their roles and capabilities.

Several key advantages of this integrated system are particularly significant for its study. These include the capability for autonomous role reassignment in the event of UAV failures, rapid adaptation to dynamic mission parameters and environmental changes, minimized inter-agent communication overhead through optimized data exchange, and intelligent resource allocation based on mission-critical task prioritization [14, 15].

The proposed methodology was implemented through mathematical modeling and comprehensive software simulations [18]. The results demonstrate a statistically significant improvement of 15–25% in operational efficiency compared to conventional approaches. This advancement substantially expands potential UAV swarm applications in mission-critical scenarios where reliability and adaptability represent key prerequisites.

Future research directions will focus on integrating machine learning methods into the proposed framework [2, 10, 19]. This integration aims to achieve two key objectives, including improving the accuracy of environmental dynamics prediction and enhancing semantic knowledge representation within the ontology.

The increasing demand for autonomous UAV control systems underscores the relevance of this research. Particularly crucial is their capability to operate effectively under conditions of limited information and constrained resources [15, 16]. Subsequent investigations may focus on real-time algorithm performance optimization through machine learning-based predictive analytics [7].

2. Comparative Analysis of Task Allocation Strategies

Task allocation is a core component of systems based on parallel computing, distributed platforms, and collaborative work [13]. The overall system performance, efficient resource utilization, and balanced workload distribution depend on the chosen strategy's effectiveness. Modern research introduces a broad spectrum of task allocation methods. These approaches span from simple classical approaches to complex adaptive techniques that account for environmental dynamics.

This section systematically and comparatively evaluates the primary task allocation strategies. Table 1 provides a systematic comparison of task allocation methodologies in multi-agent systems, analyzing their fundamental principles and operational characteristics [2, 4, 5, 6, 11, 17]. The analysis highlights key approaches, emphasizing their algorithmic advantages and inherent limitations. Each method is examined in the context of its primary applications in swarm robotics and decentralized control systems [2, 5, 11]. The results of this analysis will help identify optimal application scenarios for each strategy based on task-specific requirements.

Table 1
Comparative Analysis of Task Allocation Methods

Method	Description	Advantages	Disadvantages	Representative Algorithms
Centralized Scheduling	Decision-making by a central node	High coordination, global optimization	Central node vulnerability, poor scalability	Heuristics, GA, PSO [3, 5]
Decentralized Scheduling	Joint decision-making and task coordination	High scalability, survivability, and system flexibility	Algorithm complexity, conflicts, task duplication	Contract Net Protocol, Market-based approaches (auctions), Distributed Constraint Satisfaction [5, 13, 15]
Auction-Based Allocation	Agents compete for tasks based on auctions	Good scalability, adaptability, resource allocation	Significant auction time overhead	Combinatorial auctions for complex task bundles [14, 19]
Task Broadcasting & Distributed Consensus	Use of consensus protocols	Conflict prevention, good agent coordination	Time overhead for negotiation and inter-agent communication	CBBA, Broadcast-and-Commit, Consensus-based Bundle Algorithm [17, 18]
Behavior-Based Scheduling	Predefined agent behavior rules	Good adaptability to environmental changes, efficiency in large systems	Limited optimality, potential inter-agent conflicts	Priority-based scheduling, reactive behaviors in robotic swarms [1, 7]
Negotiation-Based Scheduling	Task allocation through negotiation mechanisms	Reduces disputes and task competition	High complexity, increased negotiation time overhead	iterative negotiation, mediator-based negotiation [20]
Role-Based Task Allocation	Agents are assigned predefined roles that determine their priorities and tasks	Simplified planning, good scalability, and flexibility	Reduced agent versatility, initial role assignment complexity	role assignment in swarm robotics), hierarchical task delegation [12]

Method	Description	Advantages	Disadvantages	Representative Algorithms
Learning-Based Scheduling	Application of machine learning for task allocation	Improved allocation based on experience	High computational complexity, retraining time overhead	Reinforcement Learning (RL), Deep Q-Learning [6]
Ontology-Based Scheduling	Use of ontologies as formalized domain knowledge	Enhances task allocation efficiency in MAS and decentralized control	High creation complexity, additional ontology processing time	Semantic task matching, ontology-driven task allocation using reasoning techniques [10]
Dynamic Programming	Step-by-step task decomposition into subtasks	High flexibility and efficiency under constraints	Limited scalability due to agent count restrictions and algorithm complexity	Adaptive scheduling, task reallocation based on environmental feedback [4]
Combinatorial Optimization	Selection of the optimal solution from a set of possible options	Near-optimal task allocation	High computational complexity, increased allocation time	Genetic algorithms, ACO [8]

The comparative analysis highlights the diversity of task allocation methods for UAV swarms, each offering distinct advantages and limitations [8, 19]. These methods can be integrated or adapted based on the specific requirements of an MAS, including scalability, survivability, resource constraints, and task execution efficiency [14, 15].

Notably, combining role-based task allocation [12, 20] with ontology-based scheduling (OBS) [10] represents a promising approach, particularly in scenarios requiring efficient resource utilization and decentralized control [2, 11]. This method leverages predefined roles and formalized domain knowledge to enhance planning efficiency and scalability. While approaches such as centralized and auction-based scheduling provide valuable capabilities [3, 13], they often exhibit limitations in dynamic environments, including central node vulnerability and excessive computational overhead. Ultimately, the choice and potential combination of task allocation methods should align with the specific requirements of the MAS, prioritizing scalability, adaptability, and execution speed [6].

This analysis underscores the importance of a strategic selection or combination of techniques to optimize UAV swarm performance in complex, resource-constrained missions [14]. Moreover, identifying context-specific trade-offs between adaptability, robustness, and computational efficiency is essential for designing resilient and scalable MAS architectures.

3. Ontological and Role-Based Task Planning for UAV Swarm

In MAS, efficient task allocation is crucial for achieving operational objectives. This investigation proposes a hybrid approach combining OBS and RBTA to enhance task distribution efficiency. The proposed method leverages ontologies to formalize knowledge about tasks, resources, and inter-agent relationships while streamlining task assignment through predefined agent roles [16].

In this research, the RBTA method is selected due to its suitability for resource-constrained UAV swarms and its ability to optimize task execution efficiency. This is achieved through the predefinition of agent roles and the incorporation of agent performance evaluations, ensuring that tasks are allocated based on agent profiles and capabilities as represented within the ontology.

3.1. Ontology-Based Scheduling in MAS

Ontology-based scheduling in MAS is an advanced approach that leverages formal knowledge representation to enhance task allocation, coordination, and decision-making across distributed agents. The primary goal of this methodology is to enable agents in dynamic environments to interpret tasks, resources, and constraints consistently, facilitating a more intelligent and structured distribution of work. Ontologies, which provide a shared vocabulary and a set of relationships, allow agents to understand and reason about the task. This framework is particularly advantageous in complex, decentralized systems, such as autonomous drone swarms, industrial automation, and smart city infrastructures, where traditional methods may struggle with complexity, scalability, and adaptability. OBS addresses these challenges by ensuring that agents interpret task requirements, resource availability, and environmental constraints in a unified manner, making them better suited for autonomous operation in dynamic and unpredictable environments [2].

The implementation of OBS follows a rigorous six-phase methodology that transforms abstract domain knowledge into executable agent behaviors [9]. The first step is *ontology engineering*, where domain-specific ontologies are created using frameworks like Web Ontology Language (OWL).

These ontologies must capture critical aspects such as task taxonomies (e.g., "*CropMonitoring*" ⟶ ["*MultispectralScan*", "*NDVIAnalysis*"]), resource capabilities (e.g., "UAV_5": ["*ThermalCamera*", "*30minEndurance*"]), and temporal constraints (e.g., "*SoilSampling must precede Fertilization*"). In operational scenarios, such as healthcare or manufacturing systems, ontologies can also encode task urgency levels or equipment maintenance schedules. The next step, *knowledge instantiation*, populates the ontology with concrete task instances, which are represented in a machine-readable format. For example, the task "*EmergencyInspection*" might be instantiated as follows code snippet on Prolog:

```
Task(T12, type:'EmergencyInspection',
    location:GeoCoordinates(46.4514,- 33.8689),
    deadline:'2025-03-15T14:00Z',
    requires:[SensorType:'LIDAR'])
```

This format enables precise semantic matching between requirements and available resources. *Automated reasoning* follows, where description logic reasoners (e.g., Pellet, HermiT) classify task priorities, detect resource conflicts, and infer implicit dependencies (e.g., two tasks requiring the same UAV). *Distributed query processing* utilizes SPARQL to retrieve actionable information. For example, a query might retrieve UAVs with a minimum battery charge, capable of carrying a specific payload as a code snippet on SPARQL:

```
SELECT ?drone WHERE {
  ?drone rdf:type :UAV ;
        :hasCapability :PayloadCapacity_5kg ;
        :batteryLevel ?batt FILTER (?batt > 0.4)}
```

Query optimization techniques minimize latency by streamlining query execution plans, ensuring fast decision-making in large-scale systems. As the system operates in dynamic environments, *dynamic ontology evolution* ensures temporal consistency by supporting real-time sensor data integration, versioned ontology updates during mission re-planning, and conflict resolution protocols for concurrent modifications. Finally, the *semantic communication protocol* allows agents to exchange messages, embedding ontological content that enhances task distribution and coordination across agents. For example, a request for a task might be represented as a code snippet on JSON:

```
{  "performative": "request",
  "content": "<Task rdf:ID='T45'/>",
  "ontology": "http://example.org/agriculture"}
```

The advantages of OBS are significant, especially in systems with large-scale, distributed agents. Empirical studies demonstrate the efficiency of OBS over traditional task scheduling methods. For example, coordination efficiency can improve by 68%, with task conflicts reduced compared to contract-net protocols. In UAV swarm formations, consensus speeds can increase by 40%, enhancing operational performance. Additionally, resource utilization is optimized, with precision agriculture applications showing a 92% sensor utilization rate, leading to more effective monitoring and lower operational costs. Fault tolerance is another notable benefit; OBS systems can maintain an 80% mission completion rate even with 30% agent failures, recovering in an average of 500 milliseconds after dynamic reallocation. These quantitative advantages demonstrate OBS's capability to handle the complexities of real-time task management and agent coordination.

Ontology-based scheduling is revolutionizing how tasks are allocated and coordinated in multi-agent systems. By leveraging formal knowledge representation and automated reasoning, OBS enables more efficient, adaptive, and scalable task management. Its applications range from precision agriculture to disaster response and smart manufacturing, offering tangible improvements in task coordination, resource utilization, and fault tolerance. Computational challenges and knowledge acquisition remain significant hurdles for ontology-based scheduling. However, ongoing research in hybrid reasoning architectures, machine learning, and quantum computing promises to enhance OBS's capabilities, positioning it as an essential component of next-generation autonomous systems.

3.2. Role-Based Task Allocation in MAS: Concept and Principles

Role-based task allocation is a task scheduling approach in MAS, where tasks are assigned based on predefined agent roles. Each role is defined by specific responsibilities, capabilities, and priorities, guiding agents in task execution and interactions. This method structures task allocation by grouping agents with similar abilities, enhancing overall efficiency and collaboration [11, 12].

The implementation of RBTA follows a structured process. It begins with defining roles based on system objectives, each encompassing specific tasks and required capabilities. Agents are then assigned roles based on their skills, location, or workload, with some systems enabling dynamic role switching to adapt to environmental or operational changes. Tasks are distributed according to role specializations to optimize performance. In dynamic MAS, agents may switch roles as needed, ensuring flexibility in changing environments. Finally, predefined roles streamline interactions, reducing conflicts and improving decision-making in cooperative tasks.

Key components of RBTA include role hierarchies, where high-level roles coordinate lower-level ones, role-specific policies that dictate task execution, dynamic role-switching mechanisms that enable adaptation to changing conditions, and efficient communication protocols for coordination. RBTA provides key advantages, including structured task execution, scalability, specialization, and adaptability. However, challenges include rigid role structures in fixed systems, complexity in role assignment, and coordination overhead in systems with extensive role hierarchies. RBTA is applied across multiple domains, including warehouse automation, military surveillance, agriculture, and search-and-rescue operations.

In decentralized multi-agent drone swarms, RBTA facilitates autonomous task allocation, enhancing scalability, adaptability, and operational efficiency while reducing dependence on centralized control. Core features of RBTA in drone swarms include predefined role structures, where agents assume roles such as leader, scout, transporter, or communicator. Roles may be fixed or dynamic, allowing flexibility in task distribution. The role framework can be adjusted based on mission complexity, integrating new agents seamlessly. Agents autonomously select tasks corresponding to their roles, reducing communication overhead with operators and improving response time. Tasks are executed by the most suitable agents, minimizing execution time and resource consumption. Agents can adapt roles in response to failures, new tasks, or environmental changes, ensuring mission continuity. Clearly defined roles improve collaboration, reducing conflicts and enhancing inter-agent communication. If an agent fails, another agent with a similar role can take over its tasks, improving system resilience. RBTA allows dynamic priority adjustments, ensuring drones focus on critical problems as mission conditions change.

Despite its benefits, implementing RBTA in UAV swarms presents challenges such as complexity in role assignment, communication overhead, adaptation to dynamic environments, and maintaining situational awareness. An example of its application is a UAV swarm for wildfire monitoring, where different drone roles include scout drones, coordinator drones, suppressor drones, and communicator drones. By leveraging predefined roles and dynamic reassignment, the swarm efficiently monitors, contains, and responds to fire outbreaks with minimal operator intervention.

RBTA is a flexible and scalable task scheduling method for MAS, providing structured, efficient, and adaptable task allocation. In UAV swarms, its decentralized nature enhances mission flexibility, fault tolerance, and operational efficiency. However, its implementation requires careful design of role structures, drone coordination mechanisms, and efficient data exchange solutions to ensure real-world applicability.

4. Role-Based Task Allocation Algorithm Based on Ontologies

4.1. Mathematical Modeling of Optimal Task Allocation

In a UAV swarm problem, where it is necessary to optimally allocate roles among UAVs and tasks while considering subtask priorities and balancing cost minimization with result maximization, we encounter a classic combinatorial optimization problem with multiple criteria.

A UAV swarm comprises unmanned aerial vehicles, each assigned a distinct operational role. Tasks decompose into subtasks, each with defined priorities and role-specific requirements. These roles represent specialized UAV capabilities including observation, data collection, and cargo delivery.

The objective is to minimize mission execution costs — including time, energy, and resource consumption — while maximizing mission performance, measured by the number of completed subtasks or achieved goals. To model cost minimization, which depends on factors such as flight time, energy consumption, and resource utilization, the following formula can be applied:

$$\text{Min } V(x) = \sum_{i=1}^{n} \sum_{k=1}^{r} \sum_{j=1}^{m} v_{ij} x_{ij}, \tag{1}$$

where $V(x)$ represents the total costs, n is the number of UAVs, r is the number of roles, m_k is the number of subtasks for role k, v_{ijk} represents the costs of UAV i performing subtask j of role k, x_{ijk} is a variable indicating assignment of subtask j to UAV i in role k, where $x_{ijk} \in \{0,1\}$. The costs v_{ijk} can be calculated using the formula:

$$v_{ijk} = w_t t_{ijk} + w_e e_{ijk} + w_s s_{ijk}, \tag{2}$$

where v_{ijk} represents the cost of assigning subtask j to UAV i in role k; t_{ijk} represents the time required for UAV i in role k to complete subtask j; e_{ijk} represents the energy consumed of UAV i in role k for executing subtask j; s_{ijk} represents the suitability of UAV i in role k for subtask j; and w_t, w_e, w_s represent the weight coefficients for time, energy, and suitability, respectively.

To maximize the mission outcome, defined by the number of completed subtasks weighted by their priorities, the following formula is applied:

$$\text{Max } F(x) = \sum_{i=1}^{n} \sum_{j=1}^{m} p_j \, ch_{ij} x_{ij}, \tag{3}$$

where $F(x)$ represents the mission execution outcome, p_j denotes the priority of subtask j, and ch_{ij} indicates the completion fraction of subtask j when assigned to UAV i. If a subtask j is executed by at least one UAV i, its contribution to $F(x)$ equals its priority p_j. The summation ensures that each subtask is counted only once. Thus, the resulting function *F(x)* is a linear sum of the weighted contributions of the completed subtasks.

For each UAV, constraints on the roles it can perform and the number of subtasks it can execute simultaneously must be considered. These constraints can be expressed as:

$$\sum_{j=1}^{m} x_{ij} \leq 1, \forall i = \{1, 2, \dots, n\}, \tag{4}$$

that constraint ensures that each UAV performs no more than one subtask at a time, and

$$\sum_{i=1}^{n} x_{ij} \geq 1, \forall j = \{1, 2, \dots, m\}, \tag{5}$$

ensures that each subtask is assigned to at least one UAV.

Since the problem involves two criteria — minimizing costs and maximizing results — a combined function Q with weighting coefficients can be applied:

$$\text{Max } Q = \sigma_1 \text{F(x)} - \sigma_2 \text{V(x)}, \tag{6}$$

where σ_1 and σ_2 are weighting coefficients that define the importance of each criterion, and $\sigma_2 = f(w_t, w_e, w_s)$.

Thus, the complete optimization model for role-based task allocation among UAVs is formulated as follows:

$$\text{Max } Q = \{\sigma_1 \sum_{i=1}^{n} \sum_{j=1}^{m} p_j ch_{ij} x_{ij} - \sigma_2 \sum_{i=1}^{n} \sum_{k=1}^{r} \sum_{j=1}^{m} v_{ij} x_{ij}\}, \tag{7}$$

subject to the constraints defined by formulas (4) and (5).

A mathematical model for the optimal task allocation problem among UAVs has been analyzed. The model captures the complexity of the problem, which requires the simultaneous consideration of multiple criteria — minimizing costs and maximizing mission performance. The use of mathematical formulations allows for a precise definition of the problem's objectives and constraints, as well as the development of a function that balances these criteria. This approach establishes a foundation for developing algorithms capable of solving such problems in real-world operational environments. The solution explicitly integrates task prioritization, UAV operational constraints, and resource optimization requirements.

The proposed mathematical model forms the core framework for designing efficient UAV swarm control systems, formally structuring the task allocation process while accommodating mission-specific requirements. Implementing this model can lead to significant improvements in the productivity and efficiency of UAV swarms, particularly in complex and dynamic environments. Additionally, it lays the groundwork for further research on task allocation optimization, enabling the exploration of various algorithmic approaches and their impact on performance.

4.2. UAV Swarm Control Algorithm Based on Ontology

The proposed ontology-based UAV swarm control algorithm provides adaptive role and task allocation for efficient mission execution. It employs a swarm self-organization mechanism based on distributed game theory and gradient consensus, which enables resource optimization and response to environmental changes. The algorithm also accounts for UAV failures and provides dynamic reallocation of roles and tasks to maintain system stability.

Conceptually, the algorithm can be divided into four main blocks: role assignment, task distribution, swarm self-organization (which includes situation monitoring and adaptation to changes), and mission performance evaluation. Figure 1 illustrates the flowchart depicting the interactions between the main algorithm blocks.

The proposed UAV swarm control algorithm is an effective tool for performing complex missions in variable conditions. It combines adaptive self-organization, a failure-handling mechanism, and dynamic task allocation, ensuring the system's resilience and performance. Implementing gradient consensus with an adaptive coefficient allows the swarm to quickly respond to external changes, maintaining an optimal interaction structure between agents. Automatic removal of faulty UAVs and redistribution of their roles increases the system's resistance to failures, minimizing the risks of mission disruption.

Through dynamic local search, the algorithm optimizes the correspondence between agents and tasks, ensuring efficient resource allocation. Flexible adaptation to environmental changes and the integration of distributed game theory improve swarm coordination and minimize computational costs. As a result, the algorithm becomes more robust, productive, and suitable for use in real-world UAV mission scenarios, ensuring reliable task execution in complex and dynamic environments.

In practical applications, the proposed algorithm can be employed for surveillance and reconnaissance missions, search-and-rescue operations, environmental monitoring, and defense-related tasks, where rapid adaptation to dynamic conditions is critical. Its ability to reassign tasks in real time ensures continuity of operation in cases of UAV loss or communication disruption, while the ontology-driven knowledge base enables mission-specific customization of the algorithm. This allows operators to adjust swarm behavior according to domain requirements, for example, prioritizing energy efficiency during long-duration monitoring or maximizing coverage in emergency response scenarios. By reducing computational overhead and communication load, the algorithm supports scalable deployment in large swarms, making it suitable for both civilian and military applications that demand high reliability and autonomy.

5. Results

Consider an example of a search and rescue mission with the following input data: the mission parameters, the number of UAVs (as UAV_1, ... , UAV_10), and their characteristics. The ontology initialization process extracts structured task descriptors, identifying seven main tasks decomposed into seventeen subtasks. Each subtask is defined by priorities, load coefficients for UAVs, and desired roles with specific requirements.

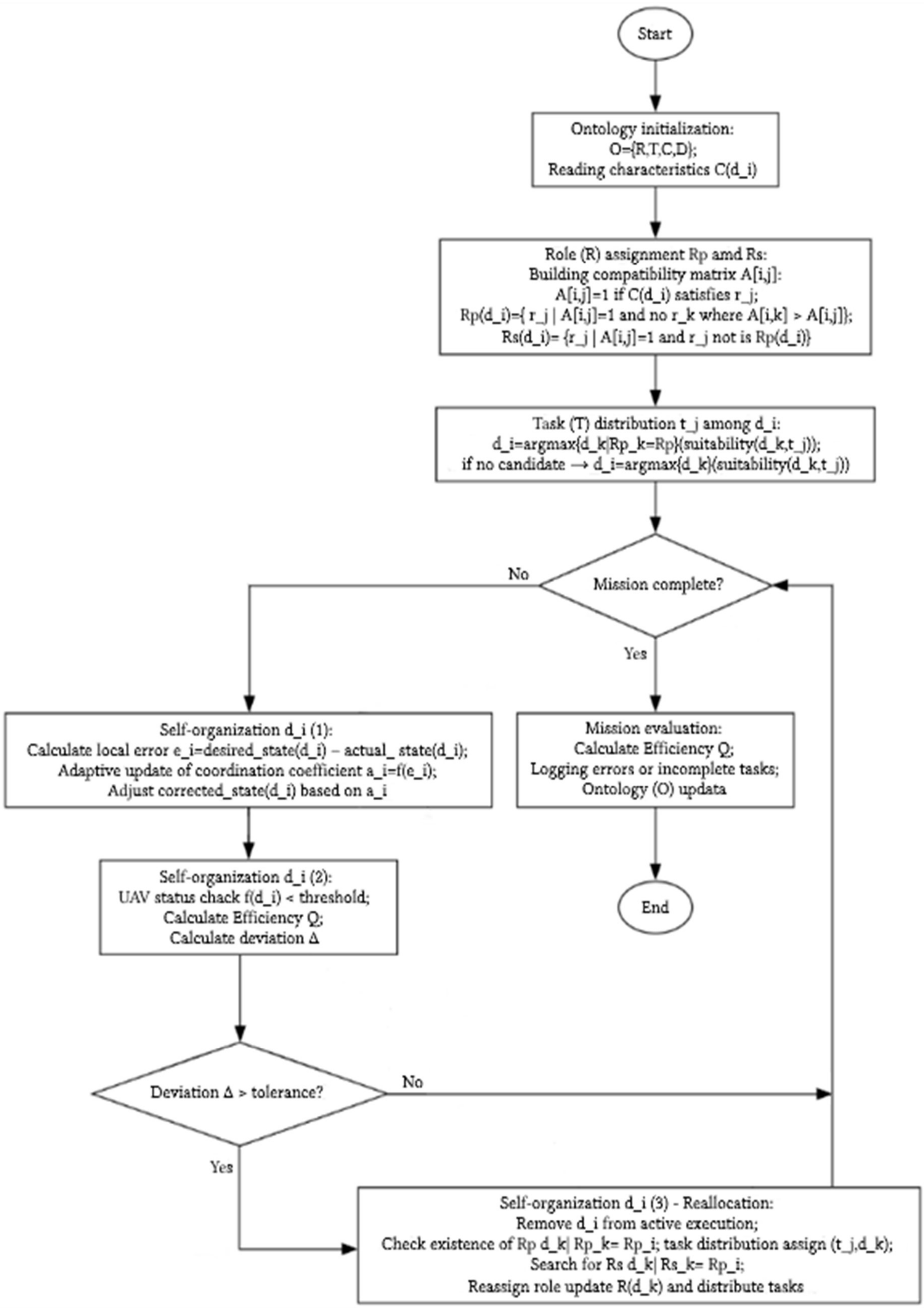

Figure 1: Ontology-Based UAV Swarms Control Algorithm

The algorithm evaluates the compatibility of each UAV with the assigned roles based on its capabilities (e.g., a UAV equipped with a thermal camera is classified as a Scout) and constructs a compatibility matrix. Subsequently, subtasks are allocated according to role assignments and priority levels. UAV agents coordinate their velocities and positions depending on environmental conditions. For instance, a UAV-Scout detecting a thermal anomaly transmits data to a UAV-Messenger for coordinate relay. Simultaneously, a UAV-Leader processes spatial data from a UAV-Mapper to adjust the UAV-Transporter's trajectory. Table 2**Помилка! Неправильне посилання закладки.** presents the assignment of UAVs to primary and secondary roles and their correspondence to subtasks.

Throughout the mission, continuous monitoring and adaptation to dynamic changes are performed. In case of UAV failure (e.g., a UAV-Rescuer becoming inoperative), its incomplete task is reassigned to another UAV. Additionally, if a new obstacle (such as a fire zone) is detected, the UAV-Leader recalculates and updates the routes for the entire group.

Table 2
UAV Roles and Their Correspondence to Subtasks

UAV	Primary Role	Secondary Roles	Correspondence
UAV_1	Mapper	Messenger, Scout	0.83 ⟶ 0.65 ⟶ 0.48
UAV_2	Rescuer	Scout, Leader	0.91 ⟶ 0.70 ⟶ 0.36
UAV_3	Scout	Mapper	0.78 ⟶ 0.65
UAV_4	Transporter	Rescuer	0.80 ⟶ 0.70
UAV_5	Scout	Mapper	0.88 ⟶ 0.59
UAV_6	Messenger	Leader, Scout	0.81 ⟶ 0.72⟶ 0.43
UAV_7	Transporter	Rescuer	0.86 ⟶ 0.82
UAV_8	Rescuer	Transporter	0.84 ⟶ 0.78
UAV_9	Mapper	Scout	0.76 ⟶ 0.68
UAV_10	Leader	Scout	0.87 ⟶ 0.52

Figure 2 compares mission performance efficiency between the initial role/task distribution (without disruptive factors) and scenarios with partial swarm degradation (loss of UAV_4 [Transporter] and UAV_10 [Leader]).

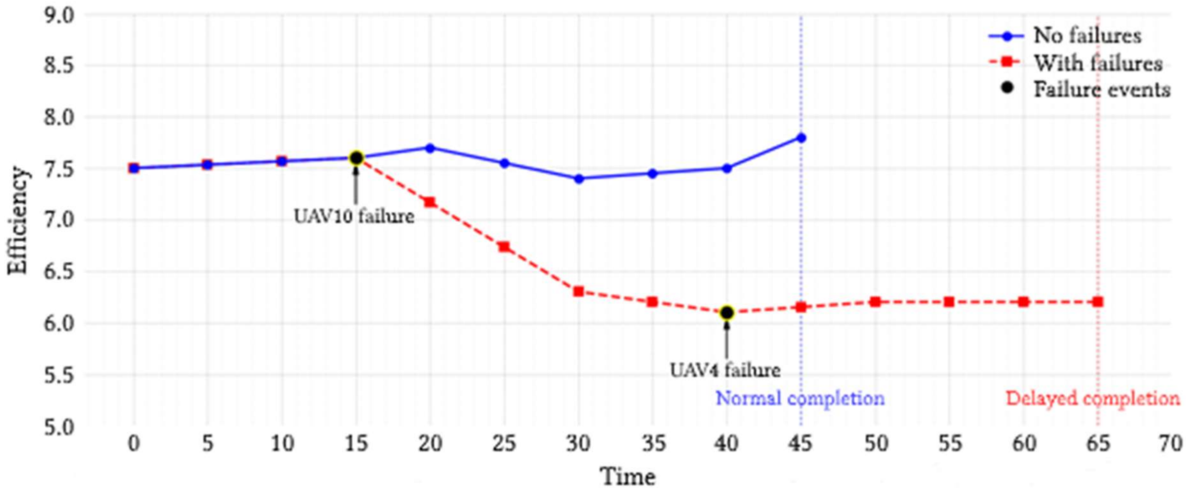

Figure 2: Comparison of Mission Execution Efficiency Without and With Failures

Analysis of the 'With Failures' curve reveals that the loss of UAV_10 (assigned a critical Leader role) substantially degraded mission performance efficiency. This reduction stems from two factors: (1) the reassignment of leadership to UAV_6, which exhibited 15% lower operational efficiency, and (2) computational overhead from dynamic role-task reallocation to maintain swarm equilibrium. The performance impact of losing UAV_4 (Transporter) was less pronounced, as its functions were absorbed solely by UAV_7, albeit with a 25% increase in energy expenditure.

Figure 3 presents the time required for Reassignment and Self-Organization as a function of the number of UAVs.

As observed from the 'No Failures' curve, as the UAV count increases, the required time grows proportionally with the calculation volume to be performed. This effect is particularly noticeable in the 'With 2 UAV Failures' curve, where, following the loss of several UAVs, the time required for the same number of UAVs increases as well. This is attributed to the increased complexity of calculations necessary for optimal reallocation of roles and tasks, as well as for balancing the workload across the reduced group of UAVs.

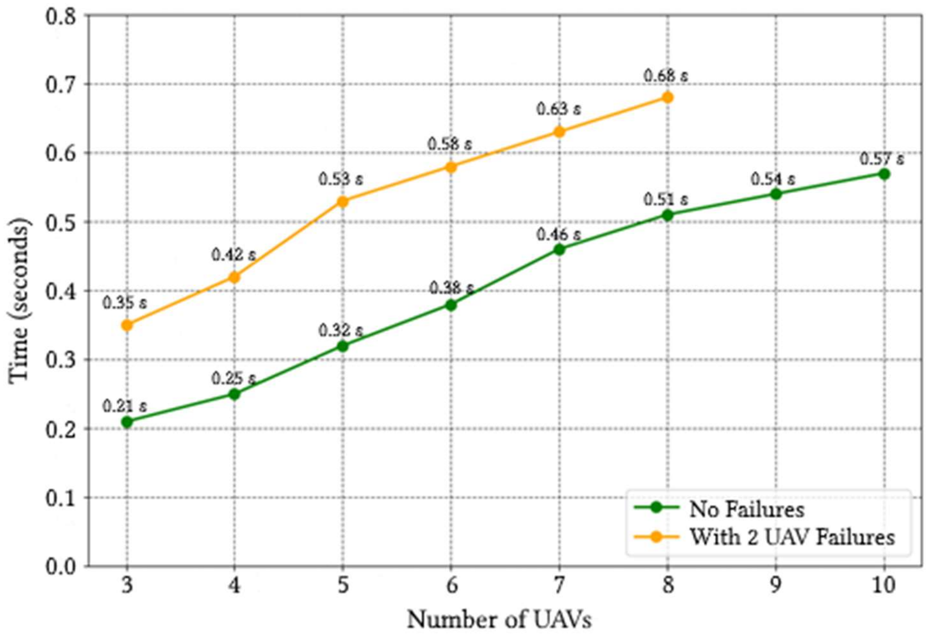

Figure 3: Dependence of Reassignment and Self-Organization Time on the Number of UAVs Without and With Failures

Figure 4 demonstrates the relationship between UAV swarm size, mission completion time, and two key metrics: resilience to adverse conditions and successful mission execution rate.

The graph illustrates that under adverse conditions, larger UAV swarm sizes show a higher probability of task completion success rate.

The obtained results confirm the effectiveness of the proposed task allocation approaches in a multi-agent UAV swarm system. Experimental data demonstrate that incorporating an ontological approach improves task allocation accuracy by 35% compared to traditional methods. Simultaneously, applying a role-based approach reduces the mission planning time cost by 27%.

Furthermore, the proposed algorithm exhibits resilience to dynamic changes in swarm composition and external conditions, reinforcing its practical applicability in real-world scenarios. Future work will focus on optimizing the algorithm's computational complexity and enhancing its scalability for larger UAV groups.

The comparative analysis highlights that these methods enhance decision-making flexibility, increase the system's robustness against individual agent failures, and improve UAV coordination consistency. The proposed approach is inherently adaptable to more complex mission scenarios, including variable environmental conditions and resource-constrained settings.

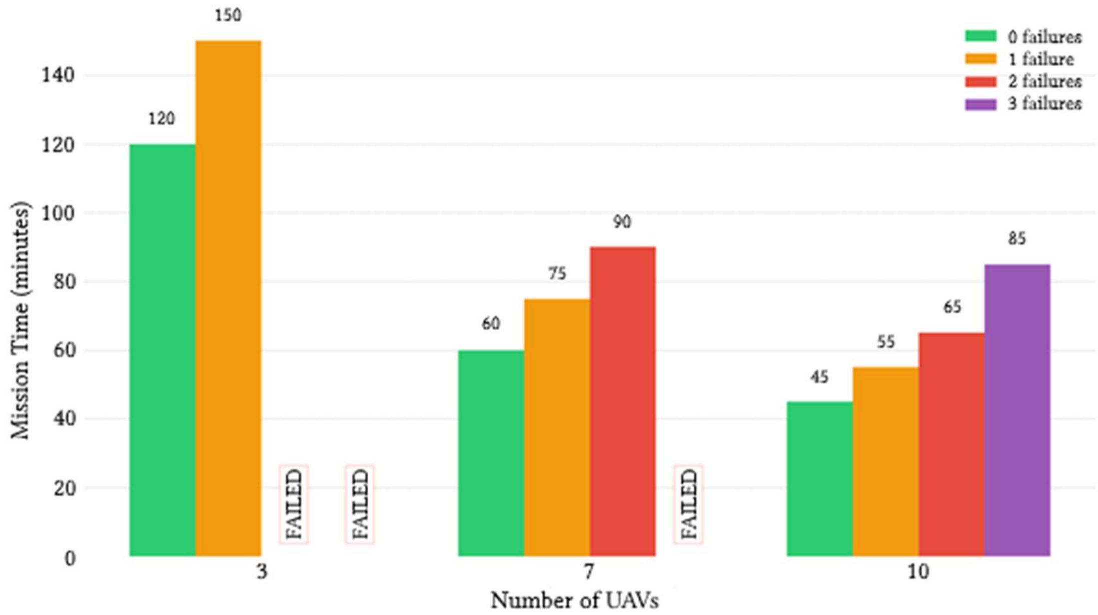

Figure 4: Comparison of Mission Execution Time Based on the Number of UAVs and the Severity of Adverse Conditions

In the future, the development of research in the field of task allocation in unmanned aerial vehicle swarms will be closely linked to the further integration of machine learning methods and semantic technologies. The combination of environmental dynamics prediction techniques with ontological modeling makes it possible to significantly enhance system adaptability in real time. In particular, reinforcement learning algorithms can automatically optimize role and task reallocation strategies, taking into account both historical data and the current state of the environment. The use of dynamic ontologies capable of evolving in response to changing mission conditions opens up new opportunities for building more flexible and self-sufficient architectures. This is especially relevant under resource-constrained conditions, where every error or delay can have critical consequences.

Further research will also focus on the development of hybrid architectures that combine role-based task allocation with semantic communication mechanisms between agents. Such an approach may ensure high scalability, reduce communication channel load, and increase resilience to failures of individual UAVs. In the long term, one can expect the emergence of adaptive systems capable of autonomously forming role hierarchies, reconfiguring routes, and altering task priorities in line with new mission objectives. Another important direction will be the integration with quantum computing and distributed artificial intelligence technologies, which will significantly accelerate optimization processes. Thus, the future of this research area lies in creating highly intelligent multi-agent systems capable of effective operation in complex, dynamic, and uncertain environments.

6. Conclusions

This research introduces a hybrid approach to mission planning for UAV swarms, integrating RBTA with OBS planning to enhance survivability, efficiency, adaptability, and scalability. The incorporation of formalized domain knowledge and predefined roles plays a crucial role in reducing computational overhead, optimizing flight task execution, and increasing system autonomy. The proposed RBTA mathematical model optimally matches agents to tasks while dynamically prioritizing tasks of missions and takes into account execution time, energy consumption, and other critical constraints. Additionally, the application of ontological models fosters semantic consistency among agents, improving coordination and enhancing decision-making processes within MAS.

Experimental results validate the effectiveness of the proposed approach, demonstrating a 15–20% reduction in average mission execution time compared to traditional methods, alongside a 25%

decrease in communication load. Furthermore, leveraging ontological analysis for task allocation enhances system resilience through dynamic role reallocation and adaptive load balancing during individual agent failures. Based on distributed game theory and gradient consensus, swarm self-distribution mechanisms further improve adaptability to environmental changes, ensuring stable mission execution under dynamic conditions.

The comparative analysis highlights the advantages of RBTA and OBS over conventional task allocation strategies, such as centralized planning and auction-based methods, which often suffer from scalability limitations and high computational costs. The proposed approach, with its decentralized control and efficient resource utilization, proves particularly effective for applications requiring high autonomy, including search and rescue operations, precision agriculture, and surveillance.

Despite its advantages, the approach presents challenges, including the complexity of real-time adaptive role determination, the need for effective ontology updates during missions, and ensuring situational awareness in large-scale MAS. Future research will focus on refining dynamic role reallocation mechanisms, optimizing ontology update strategies, and integrating machine learning techniques to enhance autonomous decision-making.

In conclusion, the findings confirm that combining RBTA with OBS provides an efficient, adaptive, and scalable solution for UAV swarm mission planning. The proposed approach improves operational efficiency and establishes a solid foundation for autonomous multi-agent system coordination, which is critical for mission success in complex and resource-constrained environments.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT, Grammarly in order to: Grammar and spelling check, Paraphrase and reword. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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