

A Bionic-Inspired Collaborative System for Manned and Unmanned Aerial Vehicles in Emergency Rescue Missions

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Abstract

To address the coordination-efficiency problem in material-demand detection and delivery tasks within a emergency-rescue scenario, this paper proposes a hierarchical and clustered coordination rule for manned aircraft/UAV systems based on a wolf-pack cooperative mechanism. First, the role division of “alpha wolf–scout wolf–attacking wolf” in wolf-pack hunting, as well as its decision-making, reconnaissance, execution, and communication mechanisms, is analyzed and mapped onto a heterogeneous cooperative system composed of a manned aircraft, reconnaissance UAVs, and logistics UAVs. Second, a hierarchical and clustered system layout is constructed, in which the manned aircraft serves as the global command and task-scheduling node, reconnaissance UAVs are responsible for regional reconnaissance and target-information feedback, and logistics UAVs perform rescue-material delivery, thereby forming a closed-loop cooperative process of “perception–decision–action.” On this basis, the state-transition rules and task-allocation logic of the manned aircraft, reconnaissance UAVs, and logistics UAVs are designed. Finally, a multi-agent simulation environment is established on the AnyLogic platform, and 20 groups of comparative experiments are conducted between the clustered layout and the conventional centralized layout. The results show that, under the scenario and parameter settings of this paper, the clustered layout achieves an average task completion rate of 91.0% and an average task completion time of 24.38 s, both outperforming the conventional layout. The results indicate that the proposed bionic clustered coordination rule can reduce task completion time and improve the completion rate of material-delivery tasks under simulation conditions, providing a reference for the design of manned aircraft/UAV cooperative rescue rules.

Keywords: Manned/unmanned aerial vehicles collaboration, emergency rescue, bionic mechanism, multi-agent simulation, task allocation

1. Introduction

In recent years, natural disasters, industrial accidents, and other emergencies have occurred frequently worldwide, posing serious threats to human life, property safety, and socio-economic development [1]. In such complex and time-critical emergency-rescue scenarios, how to conduct rescue operations rapidly and efficiently while minimizing casualties and property losses has become a key problem that urgently needs to be addressed.

Traditional emergency-rescue methods often rely on either a single manned aircraft operation mode or ground rescue forces. Manned aircraft have relatively strong payload capacity and are capable of handling complex tasks. However, in hazardous and harsh environments, such as strong typhoons or areas affected by toxic and hazardous gas leakage, their operation involves high risk and is also greatly constrained by terrain and meteorological conditions [2]. In contrast, unmanned aerial vehicles (UAVs) are flexible, lightweight, and capable of operating in complex environments. They can quickly reach disaster sites to conduct reconnaissance, monitoring, and related tasks. Nevertheless, UAVs still have certain limitations when performing tasks that require large payload transportation, complex decision-making, or high-precision operations [3]. Therefore, the

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coordinated operation of manned aircraft and UAVs, which makes full use of their respective advantages, has become an important approach to improving the execution efficiency of emergency-rescue tasks.

Emergency-rescue scenarios are complex and diverse. Disasters such as forest fires, earthquakes, and floods are sudden and highly destructive, and they may generate urgent demands for rapid reconnaissance and material delivery. Therefore, they impose high requirements on rescue efficiency and accuracy. Existing studies have explored multi-disaster scenarios [4–6]. However, resource-scheduling coordination, task-allocation closed loops, and hierarchical organization rules for heterogeneous manned aircraft/UAV formations still require further improvement.

In terms of task-allocation algorithms for emergency rescue, the Contract Net Protocol (CNP) has become an important method for human–machine task negotiation and multi-agent task allocation. Smith first proposed CNP for high-level communication and control in distributed problem solving [7]. Subsequently, related studies introduced CNP into multi-UAV task allocation, cooperative reconnaissance, and dynamic task reassignment scenarios [8,9]. However, the traditional CNP has inherent limitations in UAV cooperative task allocation. Each task usually requires a complete "announcement–bidding–award" process. The manager uses the bidding benchmark as the evaluation criterion but cannot actively screen bidders in advance, resulting in relatively low negotiation efficiency [10].

Cooperative behaviors in biological groups provide rich inspiration for the design of manned aircraft/UAV coordination rules. The division of labor observed in wolf-pack hunting has attracted particular attention. The tactical pattern of "alpha-wolf command and pack encirclement" is highly consistent with the cooperative architecture in which a manned aircraft commands a UAV swarm. In practical applications, improved wolf-pack algorithms have been applied to multi-UAV cooperative search. By simulating behavioral states such as scouting, chasing, and encircling in a wolf pack, UAVs can autonomously adjust their formations and task roles according to real-time environmental changes [11,12].

This paper introduces wolf-pack cooperative behavior rules into the CNP framework and forms a task-allocation mechanism based on "bidder-node screening and centralized optimization arbitration." This mechanism simplifies the announcement–bidding process and draws on the functional division between the "alpha wolf" and the "scout wolves." Specifically, the manned aircraft acts as the decision-making center and undertakes task-announcement management, while reconnaissance UAVs are responsible for intelligence acquisition. This forms a hierarchical and clustered system layout, which is expected to reduce invalid bids and redundant communication, thereby shortening task completion time.

2. Extraction of the Bionic Cooperative Mechanism and Establishment of the Mapping Relationship

This section systematically decomposes the cooperative hunting mechanism of wolf packs and completes the extraction process from biological intelligence to engineering rules. The study identifies the core role structure of "alpha wolf–scout wolf–attacking wolf" and the behavioral pattern of "decision-making–reconnaissance–attack–communication." On this basis, a clear mapping logic is established to transform qualitative biological mechanisms into cooperative-rule design principles that can be used in UAV systems.

2.1 Extraction of the Bionic Cooperative Mechanism

Research in animal behavior shows that wolf-pack social structures are characterized by a strict hierarchy and clear role division. The core roles can be divided into three categories: alpha wolf, scout wolf, and attacking wolf. The alpha wolf acts as the core leader of the group and is responsible for strategic decision-making and overall action deployment. Scout wolves are mainly responsible for environmental reconnaissance and path exploration, providing real-time feedback on key environmental information. Attacking wolves focus on the execution of core attack tasks and are the main force for completing key missions.

From the perspective of group cooperation, wolf packs exhibit three core characteristics: collective decision-making, division of labor, and information sharing. They exchange information through

howling, scent marking, body movements, and other channels, forming an efficient multimodal information-transmission mechanism. These group behavior mechanisms from nature provide valuable biological references for solving cooperative control problems in distributed systems, as shown in Table 1.

Table 1 – Functional analysis of wolf-pack roles

Wolf-Pack Role	Main Responsibilities	Behavioral Characteristics	Social Hierarchy
Alpha Wolf	Group decision-making and action command	Leadership-oriented and global	Highest
Scout Wolf	Environmental reconnaissance and intelligence collection	Exploratory and early-warning-oriented	Second-highest
Attacking Wolf	Cooperative attack and task execution	Execution-oriented and aggressive	Intermediate

The manned aircraft/UAV cooperative system adopts a hierarchical architecture involving three types of platforms: manned aircraft, reconnaissance UAVs, and logistics UAVs. According to related studies on multi-UAV cooperative control, such systems need to address several key technical issues, including task decision-making, motion planning, and formation control.

In terms of communication-mechanism design, UAV systems rely on data links and communication networks to exchange various types of information. Proper allocation of communication resources and optimization of network topology play a key role in the overall performance of the system. Especially in complex rescue scenarios, environmental interference is often strong, so low-latency and high-reliability transmission of key information must be ensured to meet the real-time requirements of rescue tasks.

2.2 Mapping Between Wolf-Pack Behavior and the Manned Aircraft/UAV System

Based on the systematic decomposition of wolf-pack cooperative hunting behavior, its core elements can be summarized from two dimensions: role division and behavioral pattern. In terms of role division, wolf packs present a clear hierarchical structure. The alpha wolf serves as the core of group decision-making and action command; scout wolves are responsible for environmental reconnaissance and intelligence collection; and attacking wolves undertake cooperative attack and task-execution functions.

In terms of behavioral patterns, wolf packs show typical behaviors such as group decision-making based on environmental information, systematic regional exploration, coordinated target encirclement, and real-time communication through howling. Correspondingly, the manned aircraft/UAV cooperative system also has functional hierarchy and behavioral coordination requirements. At the functional level, the system requires a command-and-control layer for global situation awareness and task planning, a reconnaissance-sensing layer for regional scanning and target localization, and a task-execution layer for precise delivery and emergency response. At the behavioral coordination level, the system requires a dynamic real-time task-allocation mechanism, a distributed environmental perception and joint-action mechanism, and an efficient and reliable information-sharing mechanism.

According to the principle of functional similarity, the roles and behavioral elements of the wolf pack can be systematically mapped to the manned aircraft/UAV system. Specifically, the decision-leading behavior of the alpha wolf is mapped to the global task allocation and dynamic scheduling responsibilities of the manned aircraft. The scouting behavior of scout wolves is mapped to the regional scanning and target localization functions of reconnaissance UAVs. The encircling and executing behavior of attacking wolves is mapped to the precise material-delivery tasks of logistics UAVs. Meanwhile, wolf-pack howling communication is mapped to inter-aircraft communication protocols between the manned aircraft and UAVs.

At the dynamic coordination level, the wolf pack's collective decision-making process is transformed into task reassignment and resource scheduling by the manned aircraft based on global situation awareness. The cooperation between scout wolves and attacking wolves is mapped to the "intelligence–action" closed loop formed by reconnaissance UAVs and logistics UAVs. The wolf pack's multimodal communication system, including long-distance howling and short-distance body language, corresponds to the hierarchical communication architecture of UAVs, in which UAV data links are responsible for wide-area communication and ad hoc networks are responsible for local information exchange.

Through the above mapping, the social structure and behavioral pattern of "alpha wolf–scout wolf–attacking wolf" are transformed into engineering-oriented cooperative-rule design principles for a manned aircraft–reconnaissance UAV–logistics UAV system. This provides a clear biological basis for subsequent system modeling and rule design. The specific mapping relationship between wolf-pack behaviors and UAV system components/behaviors is shown in Table 2.

Table 2 – Mapping relationship between wolf-pack roles and UAV system roles

Rescue System Component/Behavior	Wolf-Pack Cooperative Component/Behavior	Mapping Description
Manned Aircraft (MAV)	Alpha Wolf	The manned aircraft serves as the command center and is responsible for global decision-making and task allocation, similar to the leadership role of the alpha wolf in a wolf pack.
Reconnaissance UAV	Scout Wolf	The reconnaissance UAV is responsible for frontline reconnaissance and target search, similar to the scout wolf's exploratory and reconnaissance behavior in a wolf pack.
Logistics UAV	Attacking Wolf	The logistics UAV is responsible for material-delivery tasks, similar to the attacking wolf's role in executing key actions.
Task Allocation by the Manned Aircraft	Alpha-Wolf Decision-Making	The manned aircraft dynamically assigns tasks to UAVs according to the global situation, corresponding to the decision-making behavior of the alpha wolf to ensure efficient cooperation.
Reconnaissance Behavior	Scout-Wolf Exploration	The reconnaissance UAV performs regional scanning and target localization, corresponding to the exploratory behavior of the scout wolf and providing real-time information for the group.
Material-Delivery Behavior	Attacking-Wolf Encirclement	The logistics UAV performs material delivery,

		corresponding to the encircling behavior of the attacking wolf and enabling rapid execution of key tasks.
Information Transmission Behavior	Wolf Howling	Information is shared between the manned aircraft and UAVs through communication protocols, corresponding to the way wolves use howling for information exchange and coordination.

3. Cooperative Rule Design for Emergency Rescue

Based on the extraction of the bionic mechanism, this section focuses on the behavioral logic of the manned aircraft/UAV cooperative system and conducts refined modeling. A formal state-machine modeling method is introduced to construct complete behavioral models for the intelligent agents in the system.

3.1 Layout of the Manned Aircraft/UAV Cooperative System in Emergency Rescue

According to the practical requirements of emergency rescue, this study constructs a cooperative operation system composed of one manned aircraft and multiple UAVs, including n reconnaissance UAVs and m logistics UAVs. The system adopts a hierarchical and clustered architecture, with the main objective of improving information-transmission efficiency and task-coordination capability.

The responsibilities of each platform are defined as follows. The manned aircraft undertakes global coordination and scheduling and serves as the core command node of the whole system. Reconnaissance UAVs are responsible for regional reconnaissance tasks and real-time transmission of reconnaissance information to the command center. Logistics UAVs are mainly responsible for material delivery. In the clustered layout, m logistics UAVs are assigned to n reconnaissance UAVs to form several independent operating clusters. In the simulation setting of this paper, the system forms three independent operating clusters. In addition, all UAVs maintain direct communication links with the manned aircraft. The system layout is shown in Figure 1.

3.2 Command and Decision-Making Rules of the Manned Aircraft

According to the practical requirements of emergency rescue, this study constructs a cooperative operation system composed of one manned aircraft and multiple UAVs, including n reconnaissance UAVs and m logistics UAVs. The system adopts a hierarchical and clustered architecture, with the main objective of improving information-transmission efficiency and task-coordination capability.
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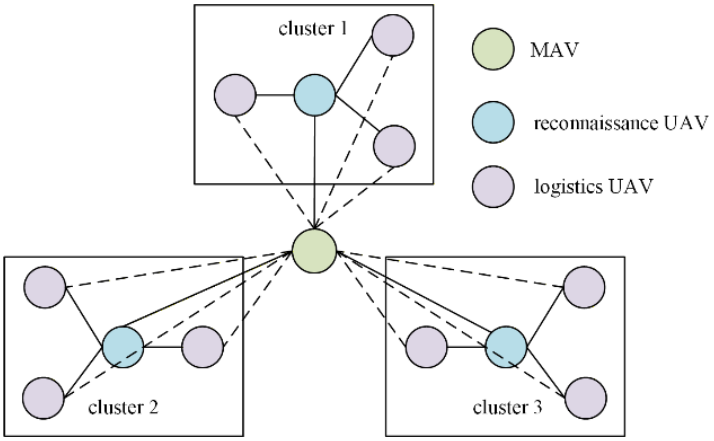


Figure 1 – Collaborative system layout

In modeling the behavior of the manned aircraft (MAV), the focus is placed on constructing the complex decision-making mechanism corresponding to its role as the command center. The behavioral model contains multiple parallel state modules, and transitions between states are triggered by events. Specifically, the manned aircraft continuously monitors environmental dynamics and integrates sensor data with information returned by subordinate UAVs, thereby constructing and maintaining a global understanding of the environment.

The core of this information-processing stage lies in multi-source data fusion, in which the credibility, timeliness, and task relevance of information need to be considered. Once new reconnaissance results are received or changes in the system state are detected, the manned aircraft immediately initiates the corresponding decision-making procedure.

In the task-allocation stage, the manned aircraft performs multi-objective matching and decision-making. First, it evaluates current task requirements, including task urgency, importance, and required resource scale. Then, it checks the status of available resources, including the real-time position, remaining operating capability, and current task load of each UAV. Based on these evaluation results, the manned aircraft solves for a suitable task-allocation scheme through a multi-attribute decision-making method. It should be emphasized that this decision-making process considers not only the current operating state of the system but also possible dynamic changes during task execution, so that the generated scheme has certain robustness and environmental adaptability.

In addition, the decision-making system of the manned aircraft incorporates an exception-handling mechanism. When the system faces unexpected situations such as insufficient resource supply, blocked task execution, or drastic environmental changes, the manned aircraft can trigger the corresponding emergency-response process. For example, in an emergency-rescue scenario, if a logistics UAV responsible for material delivery becomes unavailable due to equipment failure, the manned aircraft can quickly start task-replanning and dispatch other available resources to take over the task, thus maintaining the continuity of the rescue mission.

The manned aircraft serves as the “brain” of the system and undertakes global monitoring, task scheduling, and resource allocation. Its behavior is a continuous and cyclic decision-making process, as shown in Figure 2.

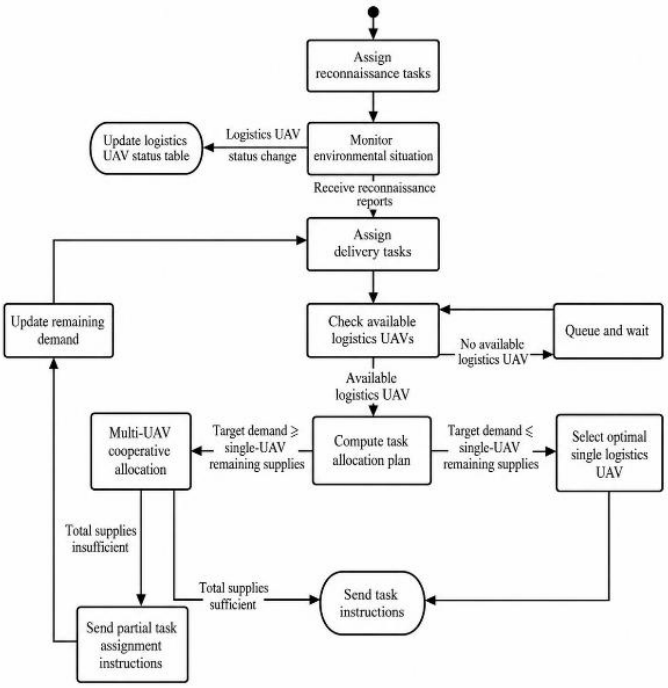


Figure 2 – State diagram of the manned aircraft work logic

a. State monitoring and data updating: The manned aircraft continuously monitors environmental conditions and receives reconnaissance reports to obtain the latest global information. At the same time, it updates the logistics UAV status table in real time and monitors the remaining supplies, current position, and task status of each logistics UAV, such as standby or executing. Any change in the status of a logistics UAV triggers the decision-making process.

b. Task generation and allocation process: Reconnaissance task allocation is performed according to global strategies or event triggers. The manned aircraft assigns reconnaissance tasks to idle reconnaissance UAVs. Delivery task allocation is started after the manned aircraft receives reconnaissance reports and confirms target demands. The first step is to screen logistics UAVs whose status is “standby” and whose remaining supplies are greater than zero.

c. Decision-making and scheme computation: If the target demand is less than or equal to the remaining supplies of a single UAV, the optimal single logistics UAV is selected, usually based on distance, remaining supplies, and related indicators. If the target demand is greater than the remaining supplies of a single UAV, multi-UAV cooperative allocation is activated to calculate an appropriate task-allocation combination.

d. Handling of insufficient resources: If the total supply in the system is insufficient, only partial task-assignment instructions can be issued. If the total supply is sufficient, complete task instructions are generated.

3.3 Regional Reconnaissance Rules for Reconnaissance UAVs

In modeling the behavior of reconnaissance UAVs, this study focuses on improving regional reconnaissance efficiency and reconnaissance quality. The behavioral model of a reconnaissance UAV adopts a hierarchical state-machine structure. The upper-level states correspond to macroscopic task phases, while the lower-level states describe specific behavioral modes. During regional reconnaissance, the reconnaissance UAV needs to balance two objectives: coverage efficiency and reconnaissance quality.

Target identification by the reconnaissance UAV adopts a multi-stage verification method. When the sensor detects a possible target, the UAV first performs preliminary identification and then approaches the target for further observation and detailed confirmation. This process makes use of the UAV’s mobility advantage. It improves the accuracy of target identification while avoiding unnecessary energy consumption. After confirming the target information, the UAV organizes the information into a standardized intelligence message and sends it back to the manned aircraft

through a reliable communication link.

The behavior of the reconnaissance UAV is a typical task-driven closed-loop process. It is mainly responsible for acquiring and returning frontline information. The detailed logic is shown in Figure 3.

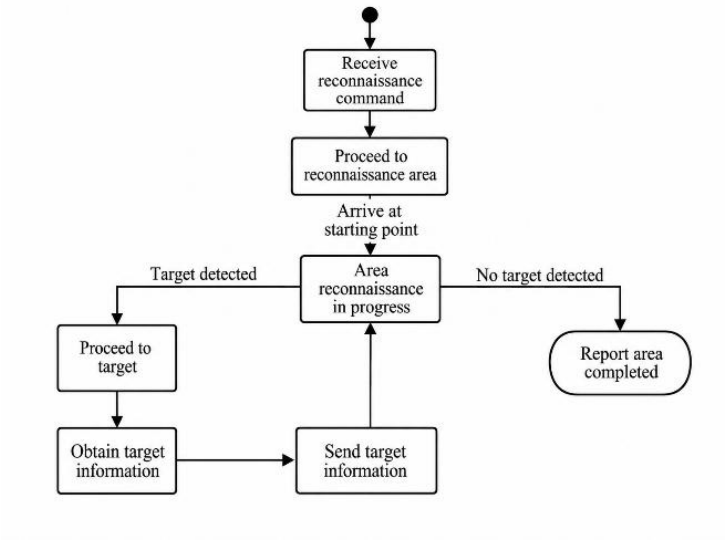


Figure 3 – State diagram of the reconnaissance UAV work logic

a. Task reception and departure: When idle, the reconnaissance UAV receives a reconnaissance command that specifies the reconnaissance area. It then immediately proceeds to that area.

b. Regional reconnaissance loop: After reaching the designated starting point, the UAV switches to the state of regional reconnaissance and continuously scans for targets.

c. Target detection: Once a valid target is identified, the UAV immediately sends the target information to the manned aircraft. If no target is found, it continues moving and conducting reconnaissance within the assigned area until the entire area is covered.

d. Task completion and reporting: After the whole area has been reconnoitered, regardless of whether a target is found, the reconnaissance UAV reports task completion and waits for a new command from the manned aircraft to start the next task cycle.

3.4 Task-Execution Rules for Logistics UAVs

The behavior modeling of logistics UAVs focuses on improving the reliability and efficiency of task execution. The state-machine model contains a complete task-management logic and can support the orderly scheduling of multiple concurrent tasks. During task execution, logistics UAVs need to consider several key factors, including path planning, energy allocation, and risk control.

For this purpose, this section designs a predictive task-execution framework to improve the operating performance of UAVs in a dynamic environment. Compared with the original expression “model predictive control,” this wording is more cautious because the current paper does not provide a complete MPC objective function, constraint set, or solving procedure.

The behavior process of a logistics UAV centers on task execution and state management. Its core objective is to complete material delivery accurately while dynamically managing its own state. The detailed process is shown in Figure 4.

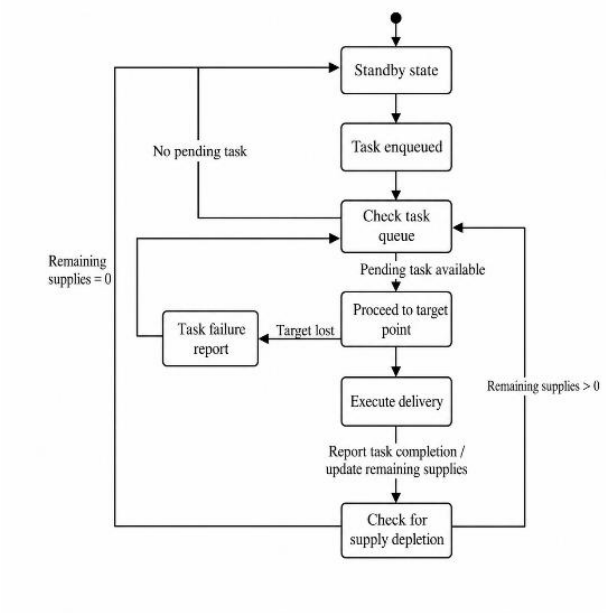


Figure 4 – State diagram of the logistics UAV work logic

a. Standby and task acquisition: The initial state is standby. The logistics UAV continuously checks its own task queue. When there is no pending task in the queue, it remains in standby. When a task assigned by the manned aircraft enters the queue, the UAV is activated.

b. Task execution and delivery: The logistics UAV takes a task from the queue and proceeds to the target point. After arriving at the target point, it executes the delivery operation.

c. State update and subsequent processing: After completing the delivery, the UAV immediately reports task completion and updates its remaining supplies. It then performs supply-depletion checking. If the remaining supplies are greater than zero, it returns to the task-queue checking state and prepares to execute the next task.

d. If the remaining supplies are equal to zero, the UAV reports its status to the manned aircraft and returns to standby to wait for subsequent instructions. The original expression “task failure report” is revised here because supply depletion after successful delivery is not necessarily a task failure.

e. Exception handling: During task execution, if abnormal conditions such as target loss occur, the logistics UAV reports task failure and exits the current task process, returning to standby or waiting for further instructions.

4. Simulation Demonstration and Data Analysis

To verify the advantages of the clustered layout proposed in this paper based on the bionic cooperative mechanism for emergency-rescue tasks, this section designs a systematic comparative experiment. The core objective of the experiment is to quantitatively compare the task-execution efficiency and success rate of the clustered layout based on wolf-pack cooperative behavior with those of the traditional centralized layout.

Experimental Scenario and Parameters

This study establishes a 1000 × 600-unit rescue scenario using the AnyLogic simulation platform. The scenario is used to abstractly simulate a disaster-affected area, as shown in Figure 5. By setting random seeds, material-demand points are randomly generated in the scenario.

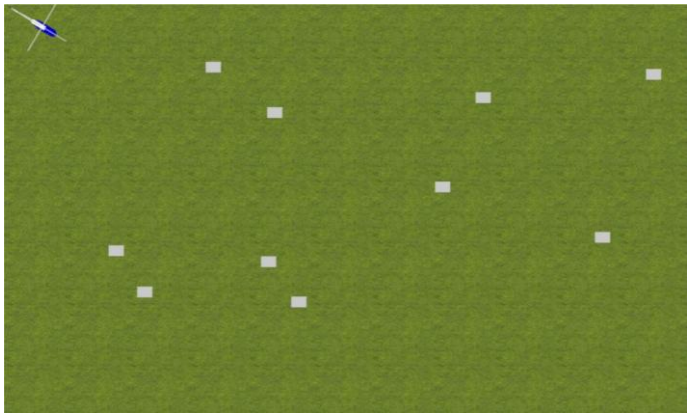


Figure 5 – Simulated rescue scenario

Task execution follows an ordered and feedback-driven closed-loop process. This process can be divided into four core stages: moving to the disaster-affected area, conducting reconnaissance tasks, assigning tasks, and delivering materials. These stages are closely connected to support efficient rescue operations.

After the task starts, the whole system enters a three-level hierarchical formation-control mode and moves toward the disaster-affected area. First, the manned aircraft, as the command center, autonomously navigates to a preset safe target point and establishes the movement direction and reference coordinates for the entire formation. On this basis, three reconnaissance UAVs follow the manned aircraft in a V-shaped formation. Each reconnaissance UAV continuously obtains the real-time position and heading of the manned aircraft and dynamically calculates its own target position accordingly, so as to maintain a stable V-shaped formation during movement.

Meanwhile, nine logistics UAVs are divided into groups of three and assigned to the three reconnaissance UAVs. Each group forms a V-shaped sub-formation. Each logistics UAV continuously tracks the position and heading of its assigned reconnaissance UAV and updates its own target point by adding a preset offset. Through this layered following mechanism, the entire formation forms a three-level hierarchical structure of “manned aircraft–reconnaissance UAV–logistics UAV” and moves cooperatively toward the target area.

After the formation arrives at the disaster-affected area, the reconnaissance UAV group separates from the logistics UAV group and starts systematic regional reconnaissance. In the simulation environment, an independent reconnaissance-path network is predefined. Each reconnaissance UAV is assigned a specific path according to its unique identifier and moves to a designated sub-region for scanning, ensuring that the area is covered without omission. Each reconnaissance UAV has an adjustable detection range and continuously detects whether material-demand points exist within its range while moving along the path.

Once a target is detected, the reconnaissance UAV immediately obtains key information such as the precise target location and the required amount of supplies. It then encapsulates this information into a message and sends it back to the manned aircraft, which serves as the command center. After transmitting the information, the reconnaissance UAV continues to execute subsequent reconnaissance tasks along the predefined path, forming a continuous information flow. This process enables the manned aircraft to maintain real-time awareness of the distribution of demands in the disaster area and provides the basis for subsequent task allocation.

The manned aircraft, as the “brain” of the system, undertakes global task allocation. It continuously monitors and receives target information returned by the reconnaissance UAVs. This information forms a dynamically updated demand map of the disaster area. When new target information is received, the internal decision-making module of the manned aircraft screens and evaluates all available logistics UAVs according to the position and demand quantity of the material-demand point.

The decision logic is as follows. If the remaining supplies of a logistics UAV can independently meet the target demand, the lowest-cost single UAV is selected to perform the task. If a single UAV cannot meet the demand but the total system supplies are sufficient, multi-UAV cooperative allocation is activated to calculate an appropriate task-combination scheme. If the total supplies of the system

are insufficient, only partial allocation instructions can be issued. If no logistics UAV is available, the task enters the waiting queue. After determining the allocation scheme, the manned aircraft generates a task package containing target coordinates and delivery instructions and sends it directly to the assigned logistics UAVs, thereby completing the bionic “perception–decision–action” chain.

Logistics UAVs are the final execution units in the rescue operation. Each logistics UAV carries a certain amount of rescue materials. After receiving a task instruction from the manned aircraft, the logistics UAV immediately interrupts its current formation-following behavior and autonomously navigates to the target point according to the coordinates in the instruction. After arriving above the target point, the logistics UAV performs material delivery, records the task-completion status, and sends it back.

After delivery, the logistics UAV updates its remaining supplies. If supplies remain, it returns to the task-queue checking state and prepares for the next task. If supplies are exhausted, it reports its status to the manned aircraft and returns to standby. During task execution, if abnormal conditions such as target loss occur, the logistics UAV reports task failure and exits the current task process. After completing delivery or handling abnormalities, the logistics UAV returns to formation or accepts the next task assignment according to new global instructions, so that the system enters the next task cycle.

The 3D simulation scenario of task execution is shown in Figure 6.

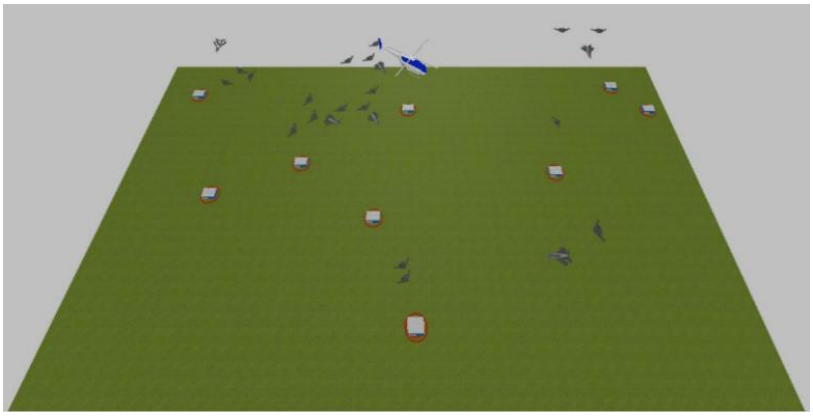


Figure 6 – Task process demonstration

To control variables and ensure fairness in the comparison, all experiments use the same underlying settings, as follows.

Material-demand point configuration: 10 demand points.

Agent configuration: Clustered layout group: one manned aircraft, three reconnaissance UAVs, and nine logistics UAVs. Every three logistics UAVs form one cluster and are guided by one reconnaissance UAV, forming three independent task units.

Conventional layout group: The types and numbers of agents are exactly the same as those in the clustered group. The difference lies in the layout strategy. In the conventional layout, the three reconnaissance UAVs independently move to predefined areas for reconnaissance, while the nine logistics UAVs are initially gathered at the center of the scenario and remain on standby. They move to target points for delivery only after receiving instructions from the manned aircraft based on reconnaissance intelligence.

Other variables: Core performance parameters, including UAV movement speed, reconnaissance range, communication delay, and supply load, are kept consistent in the two groups of experiments.

4.1 Evaluation Indicators

The experiment evaluates performance from two dimensions: effectiveness and efficiency.

Task completion rate: In a single trial, this refers to the percentage of material-demand points whose demands are successfully satisfied among all demand points. It directly reflects the task-accomplishment capability of the layout strategy.

Task completion time: This refers to the time elapsed from the beginning of the experiment to the completion of all assigned delivery tasks.

4.2 Experimental Results and Data Analysis

Based on the above experimental settings, simulation runs are conducted to obtain 20 groups of performance data for both the clustered layout and the conventional layout. To visually compare the performance of the two layouts, Figure 7 presents the comparison of task completion rate and average completion time across the 20 experimental groups. Overall, the orange bars representing the clustered layout are higher than the blue bars representing the conventional layout in most experimental groups. Meanwhile, the orange time curve corresponding to the clustered layout remains below the blue time curve. This preliminarily indicates that the clustered layout can improve task success rate while reducing task completion time.

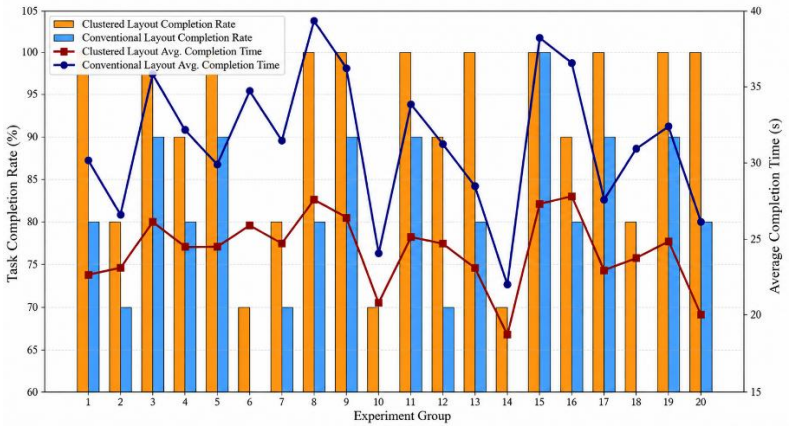


Figure 7 – Comparison of task completion rate and task completion time between clustered and conventional layouts

The task completion rates of the two layouts are compared in Table 3, and descriptive statistical analysis is conducted on the data.

Table 3 – Comparison of task completion rates between clustered and conventional layouts

Experiment Group	Clustered Layout	Conventional Layout	Experiment Group	Clustered Layout	Conventional Layout
1	100	80	11	100	90
2	80	70	12	90	70
3	100	90	13	100	80
4	90	80	14	70	60
5	100	90	15	100	100
6	70	60	16	90	80
7	80	70	17	100	90
8	100	80	18	80	60
9	100	90	19	100	90
10	70	50	20	100	80

For the clustered layout, the average task completion rate is 91.0%, with a standard deviation of 11.6%. Among the 20 trials, 11 achieve 100% completion, indicating high task reliability. For the conventional layout, the average task completion rate is 77.5%, with a standard deviation of 13.8%. Its completion rate is generally lower than that of the clustered layout.

The advantage of the clustered layout mainly comes from the forward deployment of logistics UAVs

with reconnaissance UAVs. This greatly shortens the response time of the “perception–decision–action” closed loop and avoids the time delay caused by long-distance movement of logistics UAVs from the center point in the conventional layout. As a result, more task opportunities can be captured in dynamic rescue scenarios.

The task completion times of the two layouts are compared in Table 4, and descriptive statistical analysis is conducted.

Table 4 – Comparison of task completion times between clustered and conventional layouts

Experiment Group	Clustered Layout	Conventional Layout	Experiment Group	Clustered Layout	Conventional Layout
1	22.70	30.15	11	25.13	33.82
2	23.11	26.54	12	24.69	31.20
3	26.10	35.80	13	23.11	28.45
4	24.48	32.11	14	18.79	22.05
5	24.51	29.85	15	27.27	38.18
6	25.86	34.67	16	27.81	36.50
7	24.73	31.42	17	22.99	27.59
8	27.55	39.37	18	23.77	30.90
9	26.41	36.15	19	24.86	32.32
10	20.84	24.08	20	20.08	26.10

For the clustered layout, the average task completion time is 24.38 s, with a standard deviation of 2.31 s. For the conventional layout, the average task completion time is 31.84 s, with a standard deviation of 4.98 s. The clustered layout is approximately 7.46 s faster than the conventional layout, corresponding to an efficiency improvement of about 30.6%.

As shown in Figure 8, further observation of the data distribution reveals that the advantage of the clustered layout is also reflected in higher stability. The box of the clustered layout is shorter and its whisker range is smaller, indicating that its completion times are more concentrated. By contrast, the box of the conventional layout is longer and has more upper outliers, indicating greater fluctuation in completion time and greater susceptibility to scheduling delay.

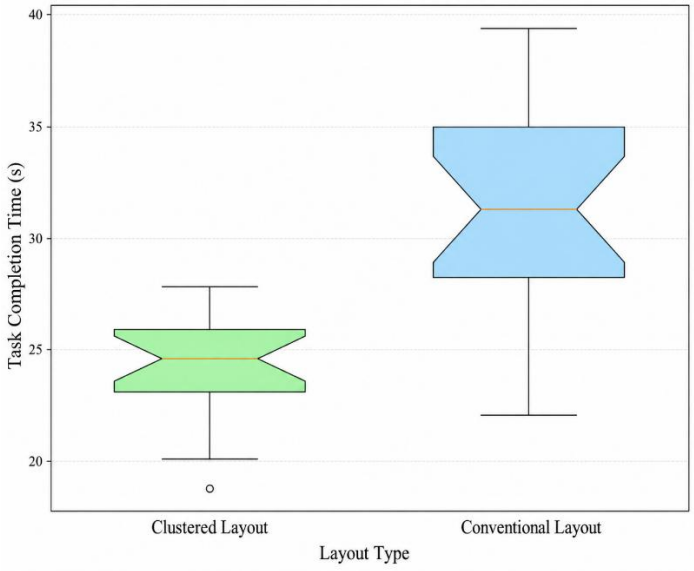


Figure 8 – Boxplot of task completion time for clustered and conventional layout

The dual advantage in efficiency and stability stems from the bionic cooperative mechanism of the clustered layout. First, parallel processing capability is improved: the three clusters are spatially

distributed and can operate in different regions simultaneously, avoiding dispatching queues caused by the centralized standby of logistics UAVs in the conventional layout. Second, travel distance is optimized: logistics UAVs are deployed forward, significantly shortening movement distance and reducing idle flight time and the uncertainty caused by it.

5. Conclusion

This study focuses on the issues of slow emergency response speed and low mission success rate in complex disaster environments and explores manned aircraft/UAV cooperative rules. By introducing a bionic perspective, the cooperative hunting wisdom of wolf packs is transformed into engineering-oriented cooperative rules. A research process of "theoretical analysis–mechanism extraction–system design–simulation verification" is established for the research problem addressed in this paper. The main work and conclusions are as follows.

First, a bionic mapping method based on the wolf-pack cooperative mechanism is proposed and verified. By decomposing the role division of "alpha wolf–scout wolf–attacking wolf" and the behavioral pattern of "decision-making–reconnaissance–attack–communication," this study establishes a mapping relationship with the "manned aircraft–reconnaissance UAV–logistics UAV" system. This provides a feasible path for transforming biological intelligence into engineering rules.

Second, a hierarchical and clustered cooperative system layout and dynamic operation rules are designed. Based on the bionic mapping, a three-level architecture consisting of a command layer, coordination layer, and execution layer is constructed. The layout strategy of "clustered management and forward deployment" is proposed to optimize the "perception–decision–action" closed-loop response process and improve the predictability and stability of the system.

Third, the effectiveness of the rules is verified through multi-agent simulation. In the rescue scenario built on the AnyLogic platform, compared with the traditional centralized standby layout, the task completion rate of the clustered layout increases from 77.5% to 91.0%, and the average task completion time decreases by about 30.6%. The simulation results show that, under the scenario and parameter settings of this paper, the proposed bionic clustered rule can reduce task completion time and improve the completion rate of material-delivery tasks.

At present, the simulation simplifies practical constraints such as communication delay and link interruption. The task-allocation algorithm mainly focuses on efficiency optimization. In future work, fairness, energy-consumption balancing, and other multi-objective constraints can be introduced. In addition, the scalability of the cooperative mechanism under larger system sizes and the use of artificial intelligence for online dynamic rule optimization deserve further investigation.

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