Research on Heterogeneous Multi-Agent Coalition Formation Method Based on Auction Algorithm

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Abstract. To enhance the tactical planning capabilities of air defense systems, this paper develops a mathematical model for the coalition formation problem involving defense and control resources. Given the uncertainty in task scenarios and the high demand for rapid solutions, a multi-round auction algorithm, inspired by the British auction model in auction theory, is proposed. This algorithm is tailored for the formation of large-scale, heterogeneous, multi-agent coalitions. It improves task efficiency, optimizes the utilization of internal resources, and effectively addresses various potential threats. Through simulation experiments, a comparison with the integer linear programming method demonstrates that the proposed multi-round auction algorithm outperforms in key metrics such as total battlefield coverage, coalition stability, and other relevant indicators.

Keywords: Auction Algorithm, Multi-agent, Coalition Formation.

1 Introduction

As real-world tasks grow increasingly complex, it becomes challenging for a single agent to complete a task independently without incurring significant costs. Multi-Agent System (MAS) [1] is widely applied to handle complex tasks in diverse domains, such as rescue operations, military reconnaissance, and strike missions [2]. The first prerequisite for accomplishing these tasks is to consider how to unite multiple agents to perform a certain task together, i.e., how to decompose the overall task and assign it to each of the agents to ensure efficient collaboration among them, i.e., forming a coalition. In MAS, Coalition Formation (CF) is an important problem for assigning different tasks.

According to [3], there are three main categories of coalition formation methods: centralized methods, self-organized (swarm intelligence) methods, and auction methods.

In centralized systems, a central authority is responsible for decision-making, often employing techniques like linear programming or heuristic search graphs to find optimal or near-optimal solutions [4]. While the architecture is simple and easy to implement, allowing for global problem-solving, it has limitations such as high communication demands on the central node, bandwidth requirements, computational load, and poor scalability [5-6]. Centralized approaches are more suitable for scenarios that are relatively simple, stable, small in scale, and where real-time performance is not critical but optimal task allocation is.

The swarm intelligence, also known as self-organizing approach, operates without a central node, relying instead on the interaction of simple behaviors from individual agents to generate overall system behavior [7]. Moritz et al. [8] explored a specific case of self-organizing reconfigurable agents engaged in resource gathering, demonstrating that group cooperation benefits all members and that optimal group size is influenced by environmental factors. Literature [9] employed a dynamic ANT federation technique f within a memetic algorithm to efficiently determine the optimal number of robots for timely task completion. While these methods are well-suited for dynamically changing environments and unexpected scenarios, they are limited in their ability to handle highly complex problems.

Auction algorithms, often used in market-based approaches [10], are popular due to their low computational complexity and high operational efficiency [11]. These methods are particularly suitable for distributed systems, with theoretical support indicating that bidders can achieve optimal task allocation [12]. Tang et al. modeled and simulated the search behavior of rescuers in disaster relief [13]. An auction-based cooperative rescue scheme was proposed to form coalitions and improve the overall performance of search and rescue efforts. Irfan et al. [14] proposed an auction-based scheme to address dynamic coalition formation in which the capabilities of coalition members can be varied and reduced at a particular stage， where coalition members with insufficient capabilities can be auctioned and replaced to meet mission requirements.

However, existing research has focused less on large-scale operations (where the number of resources exceeds 3000), despite the fact that real-world air defense system deployments often involve large-scale scenarios. These environments are characterized by a high volume of incoming targets and rapidly changing battlefield conditions, making time-efficiency more critical than absolute accuracy. Given that coalition formation is a key component of task execution in MAS and is an NP-hard problem, this paper proposes an improved multi-round auction algorithm to address the coalition formation challenge in large-scale scenarios, aiming to balance rapid response with optimal outcomes.

2 Problem Formulation

2.1 Problem Description

Before forming a coalition, our resource contains a total of M coalitions and N agents to be grouped, and the set of all the agents to be assigned is T, which contains ZH command-type agent, TC detection-type agent, and ZX task-execution-type agent. Each detection-type agent has attributes such as position, orientation angle, detection distance, detection angle, etc., which together determine the capability zone of detecting agent; and each task-execution-type agent has attributes such as position, striking radius, amount of bullets, etc., which together determine the capability zone of task executing agent.

Let the formed coalition i contains h_i command-type agents, c_i detection-type agents and v_i task-execution-type agents. According to the detection angle and detection distance of the detection-type agents, the capability zone of each detection-type agents in coalition i is written as $\{Area_{tc}(detect_1),\ldots,Area_{tc}(detect_{ci})\}$. Similarly, based on the location and strike radius of the task-execution-type agent, the capability area of each task-execution-type agent in coalition i is denoted as $\{Area_{zx}(execute_1),\ldots,Area_{zx}(execute_{vi})\}$.

2.2 Decision Variables

The decision variable is a binary matrix X where the data in the i^{th} row represents the membership of the i^{th} coalition. x_{ij}=1 indicates that the j^{th} agent is a member of the i^{th} coalition, while x_{ij}=0 represents that the j^{th} agent is not a member of the i^{th} coalition.

2.3 Objective Function

Considering the single-agent effectiveness and the global effectiveness of the overall coalition, there should be a reasonable mapping relationship between the coalition's selection of agents with the aim of maximizing the effectiveness of individual agents and the coalition's formation with the overall goal of allocating all agents to the coalition to maximize the system profit. Let the system profit of which is the sum of the individual profits of all coalitions, described in mathematical language as equation (1).

$$\begin{cases} \varphi^* = \max(\varphi_{ij}) = \max \sum_{j=1}^{N} (\sum_{i=1}^{M} (r_{ij} - c_{ij}) x_{ij}) \\ x_{ij} \in \{0,1\}, \forall i = 1,2,...,M, \forall j = 1,2,..,N \end{cases} \tag{1}$$

where the system profit $\varphi = \{\varphi_{ij} \mid i = 1,2,...,M, j = 1,2,...,N\}$, can be regarded as the difference between the allocated revenue r_{ij} and the quoted cost c_{ij}. The process of defining the revenue and cost of each agent is equivalent to defining the multi-objective optimization metrics in a combinatorial optimization problem, whose specific mathematical expressions will be presented in Section 3.1.

2.4 Restrictive Condition

In order to avoid the confusion of control authority, each agent can only be attributed to one coalition, thus ensuring the order and efficiency of task allocation within the coalition in the war, and obtaining the resource attribution constraints of the agents:

$$\sum_{i=1}^{M} x_{ij} = 1, \forall j = 1,2,...,N \tag{2}$$

In order to ensure that after a mission is assigned to a coalition, the coalition has the ability to command the internal nodes to detect and strike the target, the coalition needs to have both command-type, detection-type, and task-execution-type agents:

$$\begin{cases} \sum_{j=1}^{ZH} x_{ij} \geq 1, \forall i = 1,2,...,M \\ \sum_{j=ZH+1}^{ZH+TC} x_{ij} \geq 1, \forall i = 1,2,...,M \\ \sum_{j=ZH+TC+1}^{N} x_{ij} \geq 1, \forall i = 1,2,...,M \end{cases} \tag{3}$$

2.5 Evaluation Indicators

It is necessary to judge the goodness of coalition formation from certain evaluation indexes. Most of the previous researches have adopted the generalized calculation method [15], and there are also some practical problems that will propose special characteristic functions according to the application scenarios [16]. Based on the specificity of the battlefield environment, this subsection proposes four evaluation indicators from the perspective of how beneficial the allocation scheme is to the execution of the strike mission.

(1) Total battlefield coverage area

In the process of pre-war planning of resources, the larger the total capacity area of all alliances covering the battlefield, the better the coalition formation program is. The area of the graph is calculated using binary integration to get the total area covered by the battlefield as:

$$f_1 = \iint_{AOR_1 \cup AOR_2 \cup ... \cup AOR_M} 1 d\sigma \tag{4}$$

(2) Comprehensiveness of coalition capabilities

The mathematical expression *id* for the comprehensiveness of coalition capabilities is obtained by ranking the coalitions from smallest to largest in terms of the distance between their centers and the center of the protected strongholds to form a new coalition number:

$$f_2 = \sum_{id=1}^{M} \begin{pmatrix} \frac{1}{id}(Num(detect^{id}.type(Near)) - 1)) \\ + \frac{1}{M-id}(Num(detect^{id}.type(Far)) - 1) \\ + \frac{1}{id}(Num(command^{id}.type(Near)) - 1) \\ + \frac{1}{M-id}(Num(command^{id}.type(Far)) - 1) \end{pmatrix} \tag{5}$$

(3) Coalition stability

In order to prevent the OODA ring from breaking, the number of command-type agents within the coalition should be proportional to the sum of the number of detection-type agents and the number of task-execution-type agents, as in equation (6).

$$f_3 = \sum_{i=1}^{M} \left[| h_i - k_1 c_i | + | h_i - k_2 v_i | \right] \tag{6}$$

(4) Defense dead zone ratio

The defense dead zone rate is the ratio of the number of corners exceeding 180° in the inner corners of the outermost edge of the overall capability zone to the total number of corners, with a mathematical expression as in equation (7).

$$f_4 = \frac{num(angle_{concabe})}{num(angle_{all})} \tag{7}$$

3 Auction-based Algorithms for Solving Coalition Formation Problems

The concept of auction algorithms originates from real-world economic activities and can be categorized based on whether the auction prices are public. In auctions where bidding information is public, such as British and Dutch auctions, all bids are disclosed. In contrast, first-price and second-price sealed auctions keep bidding information private. Auctions can also be classified as single-item or multi-item auctions, depending on the number of items involved. Multi-item auctions often require the consideration of various constraints, leading to modifications and optimizations of the underlying model. In the context of this paper, the auction involves all agents, with the coalitions acting as the bidders. Since the number of agents significantly exceeds the number of coalitions, auctioning one agent at a time would result in inefficiency. Therefore, multiple rounds are incorporated into the traditional auction process, combined with a ϵϵ-slack complementary strategy to enhance performance. In each auction round, each coalition selects the agent with the highest net profit to bid on. If competition arises during the auction, the agent is allocated to the coalition with the higher bid. Before all agents are allocated, in each new round of the auction, the coalition's bid for the remaining unallocated agents increases according to specific rules.

3.1 Design of Mark-up Rules for Auction

Assuming that the coalition i pays c_{ij} for the agent j, and the revenue that the agent j can bring to the coalition is r_{ij}, then the net profit that the coalition gets after selecting the agent is r_{ij} - c_{ij}.

If there is still an unselected agent at the end of this round of auction, the next round of auction will be conducted according to the price update rule. First, calculate the optimal profit of the coalition i in this round of auction according to equation (8):

$$\omega_i = g_{ij^*} = \max_{t_j \in T}(r_{ij} - c_{ij}), t_{j^*} \in T \tag{8}$$

where j^* is the ordinal number of the agent chosen by the coalition i to obtain the optimal profit.

Then, the suboptimal profit of the coalition in this round of auction is calculated according to equation (9):

$$g_{ij_1^*} = \max_{t_j \in T}(r_{ij} - c_{ij}), t_j \neq t_j^* \tag{9}$$

where j_1^* is the ordinal number of the chosen agent corresponding to the suboptimal profit obtained by the coalition i.

Finally, the ε -slack complementarity strategy is used to obtain the cost offer of each coalition for each agent in the next round of auction:

$$c_{ij^*} = b_{j^*} + g_{ij^*} - g_{ij_1^*} + \varepsilon \tag{10}$$

where b_{j^*} is the highest bid of the agent t_{j^*} in the last round of auction, ε is the update step, which is a specific application of the " ε - complementary relaxation" strategy. And the purpose is to ensure that the bidding incremental, to prevent the iterative process from falling into a dead loop [17], the size of its value is related to the quality of the solution and the complexity of the computation, usually, the algorithm's convergence effect is better at this time. [18].

3.2 Coalition's Benefit Function

In the auction program, the benefit function of the coalition needs to be designed, and for the revenue brought r_{ij} to the coalition i by the joining of the agent t_j, the coalition detection capability, coalition striking capability, coalition compactness and other factors need to be considered.

(1) Coalition detection capability

One of the sources of detection ability of a coalition lies in the detection range of its internal detection class agents. Let $Area_{tc}(t_e)$ be the battlefield area that can be detected by the detecting agent t_e, $e=ZH+1$, $ZH+2,\ldots$, $ZH+TC$. Considering the increment of the detecting area that the joining of the agent can bring to the coalition, we can get the mathematical expression by using the double integration:

$$\Delta S = \iint\limits_{Area_{tc}(t_e)\cup Area_{tc}(i)-Area_{tc}(i)} 1 d\sigma \tag{11}$$

where $Area_{tc}(i)$ is the detectable range of the coalition i.

In actual combat, if a target in the detection range needs to be intercepted, a detection class agent needs to be designated to continuously detect the orientation and velocity of that target, which will occupy one detection channel of that agent. Therefore, the detection channel density is defined as the final coalition detection capability increment function:

$$g_1 = \frac{channel(t_e)}{\Delta S} \tag{12}$$

where $channel(t_e)$ is the number of detection channels of agent t_e. g_1 is the ratio of the number of detection channels of the agent to the incremental detection area.

(2) Coalition striking capability

The coalition striking capability comes from the concatenation of the strike range of the task executing agents (i.e., the concatenation of the capability areas of all task executing agents within the coalition) and the detection range of all detecting agents (i.e., the concatenation of the capability areas of all detecting agents within the coalition).

Let $Area_{zx}(t_p)$ be the battlefield area that the task-execution-agents can hit be the battlefield area that the agents can cover, $p=ZH+TC+1,\ldots,N$. The higher the overlap between the strike area that the agent t_p can cover and the detection area that the coalition i can detect, the greater the increase in the coalition's capability area caused by the joining of the agent, the greater the number of incoming targets that the coalition can cover, and the greater the coalition's capability of executing the tasks in the subsequent process. Mathematically, we use the intersection operation and the binary integration to measure the incremental size of the mission execution capability of the coalition i brought by the addition of agent t_p:

$$Overlap = \iint_{Area_{tc}(i) \cap Area_{zx}(t_p)} 1 d\sigma \tag{13}$$

In addition to the range overlap problem, the number of ammunition resources carried by an agent also affects the mission execution capability of a coalition. Let $Amm(t_p)$ be the number of munitions carried by the task-execution-type agent t_p, and define the density of munitions carried by the agents as the final incremental function of the coalition's task execution capability:

$$g_2 = \frac{Amm(t_p)}{Overlap} \tag{14}$$

where g_2 is the ratio of the number of munitions carried by the agent t_p to the incremental area of the coalition's capability area.

(3) The benefit function of the coalition

Considering the above two factors, the benefit function of coalition i in choosing agent t_j is integrated as follows:

$$r_{ij} = \rho_1 g_1 + \rho_2 g_2 \tag{15}$$

where $\rho_1, \rho_2 \in (0,1]$ is the two weighting coefficients with a default value of 1, with minor parameter adjustments based on the change in importance of the detection-type and task-execution-type agents in real-world situations.

3.3 Coalition's Cost Functions

In addition to the benefit function, the coalition also needs to consider the cost required to shoot the smart in order to solve the payoff equation. The cost loss to the coalition i due to the addition of the agent t_j, i.e., the initial value c_{ij}^* of the coalition's offer to the agent, is calculated from both the compactness and command load perspectives of the coalition.

(1) Coalition compactness

When the average distance between agents within a coalition is smaller, i.e., when the internal structure of the coalition is more compact, the communication cost within the coalition will be smaller. Consider the average value of the distance between each pair of agents within the coalition after the agent t_j joins as a cost function of the compactness of the coalition:

$$s_1 = \frac{\sum_{i=1}^{num_t+1} \sum_{j=i+1}^{num_t+1} dis(i, j)}{C_{num_t+1}^2} \tag{16}$$

where num_t is the number of agents in the coalition before t_j joins.

(2) Command load

When the number of resource-type agents (all agents except command-type agents) in the coalition is too high, the command-type agents will be overloaded, so the ratio of the number of command-type agents to the number of detection-type and task-execution-type agents in the coalition is considered as the command load cost function:

$$s_2 = \sum_{j=1}^{ZH} x_{ij} \Bigg/ \sum_{j=ZH+1}^{N} x_{ij} \tag{17}$$

(3) Coalition's cost function

Considering the above two factors, the cost loss of selecting agent t_j for the coalition i is integrated:

$$c_{ij}^* = \delta_1 s_1 + \delta_2 s_2 \tag{18}$$

where $\delta_1, \delta_2 \in (0,1]$ are two weighting coefficients that weigh two different dimensions and orders of magnitude of the cost function of coalition compactness and command load.

In specific applications of auction algorithms, multiple considerations that are not identical and not directly comparable are often encapsulated in the program, e.g., Gerkey et al. in the literature [19] used the difference between quality and cost to compute the utility, and presupposed that the units of the two are directly comparable. Therefore, when designing profit and cost functions that combine multiple factors, it is usually necessary to find a reasonable set of weights between the different considerations [20].

In this study, the informativeness weight method (coefficient of variation method) is used to determine the values of and to determine the indicator weights based on the amount of information contained in the indicator data, and the weights are assigned by utilizing the coefficient of variation of the data, and the larger the coefficient of variation, the larger the assigned weights. The steps of the algorithm include (1) selecting the data in the subsequent validation experiment and calculating the data set of the two indicators. (2) Calculate the mean and standard deviation of the two indicators: μ_i and σ_i. (3) Calculate the coefficient of variation: $CV_i = \sigma_i / \mu_i$. (4) Obtain the weight values: $\delta_i = CV_i \Big/ \sum_{i=1}^{m} CV_i$.

3.4 Multi-Round Auction Algorithm Process

In this study, the number of agents is much larger than the number of coalitions, which is a kind of multi-item auction, choose the British-style auction and combine with -slack complementary strategy, use an improved multi-round auction algorithm to study the coalition formation problem, the steps of the algorithm are as follows:

Step 1: Initialize the data of all kinds of relevant attributes of coalitions and agents;

Step 2: Each coalition solves the payoff equation, i.e., profit estimation for all the current agents to be auctioned;

Step 3: Each coalition selects the agent with the highest profit for itself to bid;

Step 4: Allocate the agents to each coalition according to the principle of "the highest bidder wins";

Step 5: Update the global highest bidder and the offer table of all the agents in this round of auction;

Step 6: Update the price according to equation (10);

Step 7: Determining whether all the agents have been fully allocated, if they have been fully allocated, skip to step 7, otherwise, repeat steps 2 to 6;

Step 8: Output the allocation result.

In each round of auction, the coalition evaluates the profit of the agent to be auctioned by the formula in Section 3.1, selects the bidding target and makes a bid; if more than one coalition selects the same agent, the agent is allocated to the coalition with a higher bid; if there is no competition, the agent is allocated to the coalition that made the bid. Since the number of coalitions is much smaller than the number of agents, multiple rounds of auctions are needed, and at each new round of auctions, all coalitions will raise their bids according to equation (10). The auction ends when all the agents have been assigned.

In each round of auction, each computation for each coalition can be subdivided into 3 steps to carry out, the first is the update of the global highest bidder with the offer table, and then based on the computational formula in Section 3.1 to estimate the interest of all the current unauctioned agents, to re-select the bidding target and to update the offer price, and finally to check the iterative exit condition.

4 Simulation Experiment Validation and Analysis

4.1 Parameterization

In this paper, Matlab simulation software is used to carry out simulation experiments.The main research content of this study is large-scale combat, in order to avoid overloading the command class agents, consider the appropriate number ratio to allocate the number of each type of agents. Referring to the simulation method of literature [21], the system set our resources including 160 command-type agents, 120 detection-type agents, 560 task-execution-type agents, 3320 rounds of ammunition, totaling 4080 resources, the specific classification and quantity are shown in Table 1.

Table 1. Statistics on our resources.

Types of agents	Range(km)	Quantities	Munitions carried by an agent	Total
Command		160		160
Detect	50000	60		
Detect	100000	60		120
Execute	5000	350	4	
Execute	10000	150	8	
Execute	50000	60	12	3320

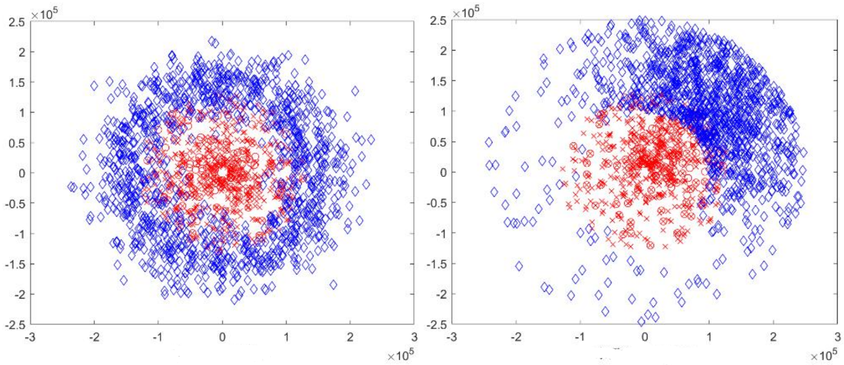
4.2 Battlefield Patterns

In the actual combat environment, when deploying our resources before the battle, we need to consider the terrain and the attack mode of the incoming target. Different terrain will result in different attack and defense difficulties, corresponding to the deployment of resources will be different; under different attack methods, the intensity of the war in different areas is different, corresponding to the pre-war deployment of resources density will be very different. In this section, three common terrain situations and two attack methods are discussed in different battlefield combinations.

Topographic Condition. Plain terrain conditions are easy to defend and easy to attack, requiring multiple protective strongholds, with all types of agents scattered in a circular pattern around the protective strongholds. In mountainous terrain, which is easy to defend and difficult to attack, only a single protection zone is considered. In river terrain, we define our agent resources to be distributed along the river, in order to prevent incoming targets from crossing the border.

Incoming Target's Mode of Attack. There are two types of attacks on incoming targets: uniform attacks and centralized attacks. In the former case, the targets are attacking at the same time without main attacking direction, corresponding to our agent resources should be evenly distributed; in the latter case, there is a main attacking direction, corresponding to our agent resources should exist in the main defense direction, to ensure that there are enough intelligent bodies to deal with the target in the main attacking direction, and at the same time, we have to prepare for the attacking of the target in the rest of the direction.

Figure 1 shows the battlefield distribution of uniform and centralized attack of incoming targets in mountainous terrain as an example.



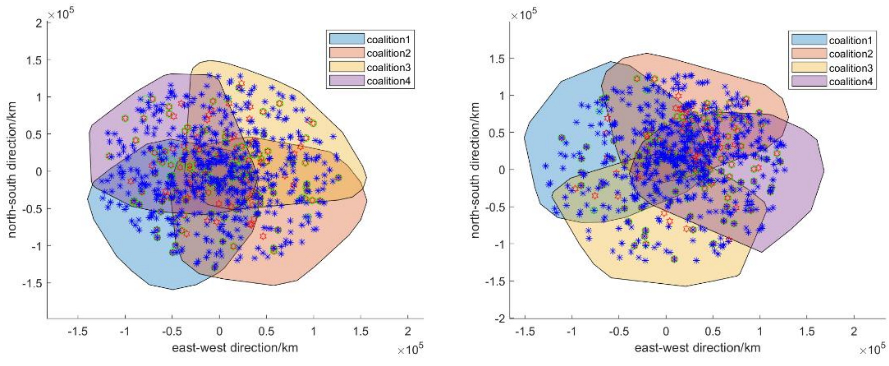
(a) distributed attack (b) centralized attack

Fig. 1. Example of a mountainous terrain deployment model

4.3 Simulation Results

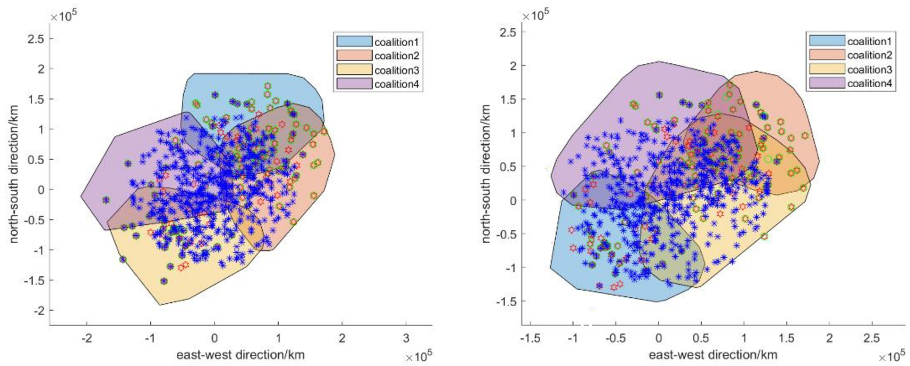
The algorithms are run under different battlefield modes respectively, and the resultant graphs obtained are shown in Figures 2 to 4.

In mountainous terrain that is easily defensible but challenging to attack, resources are organized into a central protective stronghold, with a map coordinate system established around this origin. The resources of the three agents are distributed in concentric circles around the perimeter, aligned with the direction of incoming targets. This arrangement ensures comprehensive defense coverage with no gaps, protecting the central stronghold effectively. The four coalitions formed provide uniform coverage in all directions, creating a convex polygonal capability area with minimal dead zones and enhanced overall defense. The capability zones of the four coalitions overlap, ensuring that all zones around the stronghold intersect and secure its defense. In the case of a centralized attack, it is crucial to allocate additional resources in the direction of the primary threat during pre-battle deployment.



(a) distributed attack (b) centralized attack

Fig. 2. Simulation results of mountainous terrain



(a) distributed attack (b) centralized attack

Fig. 3. Simulation results for plains terrain

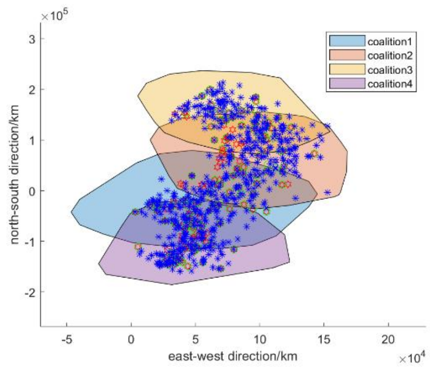


Fig. 4. Simulation results of river topography

Considering the terrain characteristics of plain terrain with open view, easy to defend and easy to attack, and needing multiple protective strongholds, two protective centers are selected, with location coordinates of (517000.25433, 50026.74686) and (-51090.87488, -50736.35726) respectively, and it can be seen from the simulation results that the overall capability area is in the form of convex polygon, with fewer defensive dead ends and There are three coalition's capability zones covering both sides of the two protected strongholds, which ensures the degree of defense in the key areas, and at the same time can alleviate the regional load balancing and munitions load balancing of each coalition. In response to the characteristics of the uniform attack, the four coalitions are more evenly distributed around the two protected strongholds to ensure that incoming targets in all directions can be detected and attacked. Under the centralized attack mode, the resources of the agents in the direction of centralized attack are more intensive, and the overlapping area of capability zones is larger in the northeastern direction where the target is mainly attacked, which is conducive to easing the pressure of the coalition's execution of the mission, and improving the quality and efficiency of the execution of intercepting the target in the direction of the main attack in terms of the overall effect.

Under river terrain conditions, resource deployment is distributed along the riverbank line, and the core element of defense is to prevent the enemy from crossing the riverbank line. Thinking from the enemy's point of view, it is easier to focus on one direction of attack to hit a gap from the opponent's defense layout, so only centralized attack is considered under this terrain condition, and the main direction of the incoming mission is the middle part along the vertical direction of the river. From the simulation results, it can be seen that the formed coalitions are arranged vertically along the river bank, two by two overlapping, located in the middle of the core position of the coalition 2 and coalition 3 area is larger, contains a larger number of agent resources, is the main force of the overall battlefield, and cooperate with each other to complete the main attack direction of the interception task. At the same time, coalition 2 and coalition 3 have a large overlap area with the corresponding neighboring coalition 1 and coalition 4, when coalition 2 and coalition 3 are overwhelmed, the tasks in the overlap area can be assigned to coalition 1 and coalition 4, which is conducive to alleviating the regional load balance of coalition 2 and 3, and improving the overall combat efficiency of the system.

4.4 Comparison Algorithm

In order to quantitatively analyze the auction algorithm is more advantageous in the application scenario of this paper, the commonly used integer linear programming method in the centralized method is chosen as the comparison algorithm, and experiments are carried out using the same data under the five different battlefield scenarios in Section 3.3, and the results of the two algorithms are compared by means of the evaluation indexes proposed in Section 1.5 to run out the results of the two algorithms. The evaluation values of the comparison algorithms are normalized as the comparison values, and the algorithms in this chapter are used as the experimental values, and the comparison results obtained are shown in Figure 5.

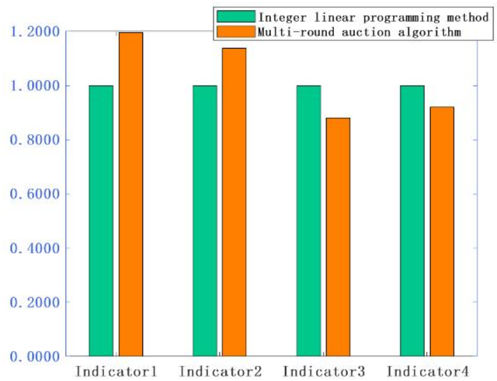


Fig. 5. Comparison chart of the two algorithms

As can be seen from the histograms of the contrasting values and the experimental values, under the resource deployment scenarios in this chapter, the value of the total area of battlefield coverage obtained by running this paper's algorithm is larger, the value of the coalition's capability comprehensiveness index is larger, the value of the coalition stability index is smaller, and the value of the defense dead-end rate index is lower. Therefore, the data of this comparison experiment shows that the overall performance of the coalition formation scheme solved by the algorithm in this chapter is better than the scheme solved by the integer linear programming algorithm.

5 Conclusion

This paper focuses on the coalition formation problem in heterogeneous multi-agent systems, developing a mathematical model tailored to the specific characteristics of the problem. A solution framework based on an auction algorithm is designed, with performance evaluated through comparative experiments conducted using Matlab simulation software. The results demonstrate the effectiveness of the proposed coalition formation scheme, confirming that the auction algorithm has strong practical significance.

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