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Collaborative Task Allocation of Heterogeneous Multi-Unmanned Platform Based on a Hybrid Improved Contract Net Algorithm

MAN ZHAO[1] AND DONGCHENG LI[2], (Member, IEEE)
[1]School of Computer Science, China University of Geosciences, Wuhan 430074, China
[2]Department of Computer Science, The University of Texas at Dallas, Richardson, TX 75082, USA
Corresponding author: Dongcheng Li (dxl170030@utdallas.edu)

ABSTRACT On the basis of investigating dynamic collaborative task allocation of heterogeneous multi-unmanned platform, a dynamic collaborative task allocation model was constructed to settle these problems in this paper. Moreover, the contract net algorithm was improved by means of mental coefficients, the blackboard model and the buffer pool mechanism; and a hybrid method of three modified contract net algorithms was applied to dynamic collaborative task allocation of heterogeneous multi-unmanned platform. As a result, not only is the task allocation efficiency raised, but outcomes of collaborative task allocation become more reasonable. As demonstrated by relevant laboratory findings, the corresponding performance is significantly boosted.

INDEX TERMS Heterogeneous multi-unmanned platform, collaborative task allocation, contract net algorithm, mental coefficient, blackboard model, buffer pool mechanism.

I. INTRODUCTION

As is well-known, unmanned platforms are characterized by fast responses, low costs, fewer casualties and the ability to complete demanding tasks in a harsh condition. Gradually, they turn into one of the important means to process various tasks in complex and severe environments, including scouting, striking and rescue. As the working environment becomes increasingly complicated, a single-unmanned platform can no longer satisfy more task demands due to certain limitations, such as insufficient individual abilities and simple execution approaches [1]. In this context, an inevitable tendency of unmanned platform-based task allocation technique research is to investigate how heterogeneous unmanned platforms can be reasonably allocated in a dynamic condition to complete collaborative tasks rapidly and effectively [2].

Under circumstances that specific constraints are known and tasks dynamically change, dynamic collaborative task allocation of the heterogeneous multi-unmanned platform is a process distributing tasks to respective unmanned platforms where these tasks can be collaboratively executed on the premise of completing the tasks at the lowest cost. In a complex and dynamic environment with time and resource constraints, some collaboration problems, such as task planning, action coordination and conflict resolution, need to be solved for the multi-unmanned platform with limited time and resources [3]–[5].

Targeting at the dynamic allocation of collaborative tasks on the heterogeneous multi-unmanned platform, a dynamic collaborative task allocation model was established in this study. In addition to fully analyzing actual objectives and constraints for the heterogeneous multi-unmanned platform executing tasks collaboratively, an improved contract net algorithm was designed and implemented. Moreover, such an improved algorithm is applicable to dynamic collaborative task allocation of the heterogeneous multi-unmanned platform. Then, experiments and analyses were made, verifying the feasibility of the algorithm in the multi-unmanned platform based dynamic collaborative task allocation. Furthermore, task allocation outcomes generated by improved and unimproved contract net algorithms were compared and analyzed. It turns out that the modified algorithm proposed here is both valid and superior to the unimproved algorithm.

II. DYNAMIC COLLABORATIVE TASK ALLOCATION PROBLEMS FOR MULTI-UNMANNED PLATFORM

Generally, dynamic collaborative task allocation problems of the heterogeneous multi-unmanned platform can be

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described as follows. In the context of N unmanned platforms and M tasks, the former consists of unmanned aerial vehicles (UAV), unmanned ground vehicles (UGV) and unmanned airships. Among them, UAV is applicable to scouting and striking tasks, UGV to transporting and scouting tasks, and unmanned airships to transporting and striking tasks. The result of dynamic collaborative task allocation should be generating a task execution sequence with the highest overall system efficiency provided that constraints of different unmanned platforms are satisfied.

Moreover, collaborative tasks can be principally divided into two categories. One is the joint task with temporal relations that requires different execution capabilities, primarily including the scouting-striking task. Besides, a joint task can break up into a scouting sub-task and a striking sub-task individually. As the scouting sub-task serves as a predecessor task of the striking sub-task, it must be executed to complete objective monitoring before the striking sub-task starts. The other is the tasks that should be executed with the same capability, primarily the transporting task. Since the transport volume required by such a task exceeds the upper limit of load capacity of a single unmanned platform, it needs to be completed by a multi-unmanned platform jointly.

A. DATA DESIGN

Data design includes the design for task attributes, UAV attributes, UGV attributes, unmanned airship attributes and task planning:

First, task attributes consist of task sequence numbers, collaborative task sequence numbers, task types, longitude and latitude of a task coordinate, the earliest and the latest start time of a task, task durations, task platform types, task requirements, and task distance. As this study is targeted at dynamic tasks, tasks are randomly generated within a certain range of the base to simulate the advent of dynamic tasks in real scenarios; and the start time of the task is also random here. The unmanned platform should, while satisfying both task and platform constraints, reach a task site within the duration from the earliest to the latest start time as required; after the arrival, it should stay at the site to execute the corresponding task. As for its dwell time, it depends on the task duration. Once the task is completed, the unmanned platform returns to the base. Only unmanned platforms successfully completing all steps are considered being capable of accomplishing the task.

Second, UAV attributes include UAV sequence numbers, UAV types, the maximum flight speed, the minimum flight speed, the maximum range, and the maximum loading capacity.

Third, UGV attributes refer to UGV sequence numbers, UGV types, the maximum speed, the minimum speed, the maximum range, and the maximum loading capacity.

Fourth, unmanned airship attributes include sequence numbers, types, the maximum flight speed, the minimum flight speed, the maximum range, and the maximum loading capacity of such airships. To be specific, they can be described as follows.

Finally, task allocation planning covers the plan sequence numbers, sub-plan sequence numbers, platform sequence numbers and task sequences.

B. MATHEMATICAL MODEL

Research on dynamic collaborative task allocation of multi-unmanned platforms is targeted at various scouting, transporting and striking tasks that need to be executed by unmanned platforms. Regarding resource distribution and unmanned platform scheduling-related problems during task allocation, they should be investigated based on the multi-unmanned platform in combination with a problem model. Through the efficient and reasonable allocation of multiple task objectives required, not only is task allocation speed improved, but the dissipation of the unmanned platform can be lowered. In this way, the overall system efficiency is enhanced. On this basis, a scientific dynamic collaborative task allocation model needs to be constructed based on the multi-unmanned platform, transforming the problem of multi-unmanned platform based dynamic collaborative task allocation into a combinational optimization problem of rapidly pursuing the optimal under limitations of different constraints [6]. This section primarily introduces the rational mathematical model built for task allocation.

1) TASK ALLOCATION PROBLEM MODEL

Problem description: It is assumed that there are M target tasks and N unmanned platforms at present. Such N unmanned platforms compose a multi-unmanned platform system. This system is responsible for the scheduling of various unmanned platforms to meet the demands of M target tasks. While an unmanned platform is able to execute a single task at the same time, the proposed system allows multiple unmanned platforms to execute the same task collaboratively. In other words, the system can allocate a task to multiple unmanned platforms, in which case, the task is collaboratively completed by these platforms. During task allocation, the overall system load should remain as balanced as possible, making sure that the number of idle platforms is proper and pursuing high availability, high efficiency and low energy consumption as a whole.

2) MODEL DEFINITIONS

M: The number of target tasks

N: The number of unmanned platforms

$T = \{t_1, t_2, t_M\}$: The set of task objectives

$U = \{u_1, u_2 \ldots, u_N\}$: The set of unmanned platform resources

X_{ij} : It, being 0 or 1, refers to task allocation. $X_{ij} = 1$ means that jth task is assigned to ith unmanned platform; otherwise, $X_{ij} = 0$.

$Time_{ij}$: It refers to time consumed of a task, that is, the total duration consumed by ith unmanned platform that executes jth task after the task is assigned to this platform. In a case where $X_{ij} = 0$, $Time_{ij} = 0$.

$Energy_{ij}$: It refers to energy consumption of a task, that is, the amount of energy consumed by ith unmanned platform that executes jth task after the task is assigned to this platform. In a case where $X_{ij} = 0$, $Energy_{ij} = 0$.

Com_{ij} : It is the cost of communication required by assigning jth task to ith unmanned platform; and this cost is figured out based on the total number of negotiations during the allocation of the jth task.

E_i : It refers to the total amount of energy carried by the ith unmanned platform.

According to the above definitions, inherent constraints of the model are analyzed. As required, the total energy consumed by an unmanned platform executing the corresponding task cannot exceed the total amount of energy carried by this platform:

$$Energy_{ij} \leq E_i, \quad \forall i \in U \tag{1}$$

A task can be allocated to a single or multiple unmanned platform(s). More specifically, when a task is assigned to multiple unmanned platforms, it signifies that this is a collaborative task:

$$\sum\nolimits_{i=1}^{N} X_{ij} \geq 1, \quad \forall j \in T \tag{2}$$

The unmanned platform is able to execute a single task at the same time:

$$\sum\nolimits_{j=1}^{M} X_{ij} = 1, \quad \forall i \in U \tag{3}$$

3) OBJECTIVE ANALYSIS

Concerning dynamic collaborative task allocation problems of the multi-unmanned platform, the overall system objective can be described as follows. For M tasks given, a proper allocation scheme is achieved, making sure that the minimum total system energy consumption is required provided that the number of tasks completed is as large as possible. Therefore, optimization objectives of the above-mentioned problems are analyzed by taking four factors into comprehensive consideration, including the total number of tasks completed, the total time consumption, the total energy consumption and the total cost of communication of the system.

Firstly, the total number of tasks completed is considered. For a collaborative task, both time and site are random. It may conflict with other tasks, making it difficult for an unmanned platform to execute this task and eventually leading to task failures. For this reason, the number of tasks executed should be as large as possible during the dynamic allocation of collaborative tasks.

$$f_m = \frac{M'}{M} \tag{4}$$

where, M' represents the total number of tasks completed by a system; and M is the total number of tasks.

Secondly, the total time consumption, the total energy consumption and the total cost of communication of the system are considered, obtaining three cost estimation functions below:

$$f_1 = \sum\nolimits_{i=1}^{N} \sum\nolimits_{j=1}^{M} (Time_{ij} \times X_{ij})/Time' \tag{5}$$

$$f_2 = \sum\nolimits_{i=1}^{N} \sum\nolimits_{j=1}^{M} (Energy_{ij} \times X_{ij})/Energy' \tag{6}$$

$$f_3 = \sum\nolimits_{i=1}^{N} \sum\nolimits_{j=1}^{M} (Com_{ij} \times X_{ij})/Com' \tag{7}$$

where, Equations (2.5), (2.6) and (2.7) express the cost of time, the cost of energy and the cost of communication consumed by all unmanned platforms executing a task during its allocation, respectively. Moreover, $Time'$, $Energy'$ or Com' refer to the maximum cost of time, energy or communication incurred by the system in the worst cases.

Therefore, the corresponding objective function can be expressed as follows:

$$F = max \sum\nolimits_{i=1}^{N} \sum\nolimits_{j=1}^{M} [\varphi f_m + \omega(1 - \alpha f_1 - \beta f_2 - \gamma f_3)] \tag{8}$$

where, f_m stands for task completion rate, and f_1, f_2 and f_3 respectively for cost estimation functions. They can be utilized to figure out system energy consumption. α, β and γ are all cost weights, representing proportions taken by different costs in the system. φ and ω represent the system's preference for the number of tasks completed and energy consumption, indicating the system is inclined to either a larger number of tasks completed or lower energy consumption during task allocation; in this case, normalization is also conducted.

$$\alpha + \beta + \gamma = 1 \tag{9}$$

$$\varphi + \omega = 1 \tag{10}$$

C. MODEL ANALYSIS

As stated above, dynamic collaborative task allocation of the multi-unmanned platform is a NP-hard problem. When the number of unmanned platforms and tasks gradually increases, the time consumed for obtaining a more optimal solution increases accordingly. According to the requirements of dynamic task allocation, the speed of solving of the algorithm should be real-time. For this reason, Centralized Voronoi Tessellation, commonly used to settle task allocation problems, becomes incompetent. Although a distributed algorithm is not excellent at obtaining more optimal solutions, it is especially suitable for such an NP-hard problem thanks to its instantaneity and robustness. By comprehensively comparing and analyzing various algorithms, the contract net algorithm is selected to solve dynamic allocation problems of collaborative tasks in this paper.

III. DYNAMIC ALLOCATION ALGORITHM DESIGN

In this study, a dynamic allocation model is built for collaborative tasks. By analyzing characteristics of collaborative task planning problems of the multi-unmanned platform, the contract net algorithm is improved based on the mental coefficient [7], [8], the blackboard model [9] and the buffer pool mechanism [10], proposing improvement strategies for different stages. At last, the hybrid improved contract net algorithm was adopted to settle dynamic allocation problems of collaborative tasks on the multi-unmanned platform.

A. CONTRACT NET ALGORITHM

The main concept of the contract net algorithm (CNA) is to use contract signing procedures in the market for reference. Therefore, its principle can be rather simple and the algorithm itself is easy to implement. However, CNA requires a high negotiation cost, but produces low efficiency due to its negotiation mechanism. Additionally, this algorithm consists of two roles. One is the administrator distributing tasks; and the other is the participant accepting tasks. Both of them are involved in three key links of CNA, that is, the invitation for bid, submission of tender and winning the bid. When a new task appears, the administrator distributes the task for bidding among all participants. Then, participants begin to judge whether they have the ability to accomplish the task and then make a decision to submit a tender or not. If they decide to do so, a tender including their personal information is generated and submitted to the administrator. At this point, the process of submission of tender is completed. After all tenders are received, the administrator begins to assess them. In line with relevant assessment criteria, the administrator selects and authorizes a participant who is most appropriate for the corresponding task. By this time, the participant is notified of winning the bid by the administrator. Next, a contract will be signed between both parties, specifying that the task will be executed by this participant and the participant should give feedback to the administrator after the task is completed.

Specific procedures of CNA are described as following:

Step1: A collaborative task is created randomly.
Step2: An administrator distributes this task to all unmanned platforms and invites for bid.
Step3: Unmanned platforms begin to evaluate task requirements based on their own abilities; and if qualified, the unmanned platform generates a tender including personal information (e.g., self-capability) and submits the tender to the administrator.
Step4: If the administrator does not receive any tender, this indicates that no unmanned platforms are competent for this task and the algorithm ends; otherwise, the administrator selects and authorizes an unmanned platform obtaining the highest evaluation score based on the tenders.
Step5: If the unmanned platform with the maximum evaluation score refuses to accept the authorization, the administrator goes back to Step 2 and selects another unmanned platform; otherwise, a contract is signed and the corresponding unmanned platform begins to execute the task.
Step6: If the unmanned platform fails to execute the task smoothly, it can act as a new administrator and go back to Step 2 to release this task again; otherwise, information of completing the task should be reported back to the administrator and the algorithm ends.

B. IMPROVED CONTRACT NET ALGORITHM BASED ON MENTAL COEFFICIENT

The strategy of CNA is to simulate procedures of tendering and bidding. Therefore, indiscriminate broadcasting is carried out by the administrator who needs to distribute a task in order to make sure that all participants can receive bidding information. In this case, traffic of bidding broadcasting is in direct proportion to the number of participants in the system. The larger the size of this system is, the higher the cost of negotiation will be. Once a task requires repeated negotiations, the corresponding negotiation cost may be in exponential growth. In addition, different types of collaborative tasks require different types of unmanned platforms. For this reason, it is extremely unreasonable for the bidding information to be broadcasted to all unmanned platforms. Considering this, a mental coefficient is introduced in CNA to lower the cost of negotiation and also enable the system to identify heterogeneous unmanned platforms more efficiently, so that a proper unmanned platform can be rapidly selected to call for bids.

Mental coefficient embodies characteristics of participants, such as their attributes, willingness, historical behavior and interactive relationship. It can be used by the administrator as the basis for the selection of tenderers. Since different metal coefficients have different emphases, a particular type of mental coefficient may be designed according to a specific scenario. Here, six types of mental coefficients were designed in order to make sure that they can fully reflect the properties of unmanned platforms. In addition to credibility, robustness and matching degree that objectively reveal inherent attributes of these platforms, another three mental coefficients are also presented from the perspective of the administrator, that is, urgency, busyness and risk tolerance that can be used to determine whether an unmanned platform is suitable for the corresponding task.

Mental coefficient, as the basis used by an administrator to select a proper participant during bidding, comes into play during the invitation for bid. In terms of mental coefficient update, it takes place after the task is completed by the corresponding unmanned platform. Hence, procedures of the improved CNA based on mental coefficient (MC-CNA) can be detailed as follows:

Step1: The mental coefficient is initialized.
Step2: A collaborative task is created randomly.
Step3: An administrator distributes the task to qualified unmanned platforms according to the mental coefficient and invites for bid.
Step4: Unmanned platforms begin to assess requirements of the task based on their capabilities; and the unmanned platform qualified generates a tender that covers its personal information (e.g., self-capability) and submits the tender to the administrator.

Step5: If the administrator does not receive any tender, this indicates that no unmanned platforms are competent for this task and the algorithm ends; otherwise, the administrator selects and authorizes an unmanned platform obtaining the highest evaluation score based on the tenders.
Step6: If the unmanned platform with the maximum evaluation score refuses to accept the authorization, the administrator goes back to Step 2 and selects another unmanned platform; otherwise, a contract is signed and the corresponding unmanned platform begins to execute the task.
Step7: If the unmanned platform fails to execute the task smoothly, it can act as a new administrator confirming task failure, updating the corresponding mental coefficient and going back to Step 3 to release this task again; otherwise, information of completing the task should be reported back to the administrator and the mental coefficient should be updated at the same time; at this point, the algorithm ends.

C. IMPROVED ALGORITHM OF CONTRACT NET BASED ON BLACKBOARD MODEL

With respect to CNA, the cost of negotiation is mainly incurred when an administrator negotiates with participants. Essentially, many communication resources are consumed during the negotiation, because unmanned platforms are incapable of possessing global information in a distributed architecture and data necessary for algorithmic solving must be acquired through constant negotiations. To reduce unnecessary negotiations generated by obtaining other participant information in a system, the blackboard model was used for reference here to construct an information sharing data center, providing communication support for the multi-unmanned platform.

As a parallel information sharing data structure, the blackboard model has the ability to solve collaborative problems among multiple computational entities in the field of distributed artificial intelligence (DAI), realize individualized expressions of the heterogeneous multi-unmanned platform, and thus provide communication support for the multi-unmanned platform. In this model, a blackboard is a database used to store data, and transmit information and processing methods. As a global work area of a system, the blackboard may form multiple information processing layers from top to bottom according to different knowledge areas that it deals with, and performs unified management of these layers. In addition, the blackboard is provided with a control unit in charge of task allocation and blackboard information update for the unmanned platform. All unmanned platforms need to report their own data to this unit, thus realizing information sharing.

If the communication links of unmanned platforms work well and have enough bandwidth, and the unmanned platforms are able to communicate with any node in the corresponding system, it would be unnecessary to select an unmanned platform with rather strong communication capabilities as the specified center. In order to make sure that the blackboard model is more applicable to the proposed algorithmic model, the blackboard is not bound to certain unmanned platform, but is maintained by an administrator distributing tasks. Whenever the administrator needs to release a task, it contacts the previous administrator and acquires information in the current blackboard; then, based on the information, it calls for bids, thus reducing the negotiation frequency.

The improved algorithm of contract net based on blackboard model (BM-CNA) can be detailed as follows:

Step1: A collaborative task is created randomly.
Step2: An administrator builds a blackboard to record information of various unmanned platforms; if the current task is the first task in the system, the initialized unmanned platform data are added in the blackboard; otherwise, the administrator distributing the task takes the responsibility to request information in the blackboard of the previous administrator.
Step3: The administrator distributes this task to all unmanned platforms and invites for bid.
Step4: Unmanned platforms begin to evaluate task requirements based on their own abilities; and if qualified, the unmanned platform generates a tender including personal information (e.g., self-capability) and submits the tender to the administrator.
Step5: If the administrator does not receive any tender, this indicates that no unmanned platforms are competent for this task and the algorithm ends; otherwise, the administrator selects and authorizes an unmanned platform obtaining the highest evaluation score based on the tenders.
Step6: If the unmanned platform with the maximum evaluation score refuses to accept the authorization, the administrator goes back to Step 2 and selects another unmanned platform; otherwise, a contract is signed and the corresponding unmanned platform begins to execute the task; in addition, the parameter information of the unmanned platform needs to be sent to the administrator to update the corresponding blackboard.
Step7: If the unmanned platform fails to execute the task smoothly, it can act as a new administrator and go back to Step 2 to release this task again; otherwise, information of completing the task should be reported back to the administrator and the algorithm ends.

D. IMPROVED CONTRACT NET ALGORITHM BASED ON BUFFER POOL MECHANISM

For the original CNA, an administrator negotiates with multiple participants. Therefore, resources involved in bidding are temporarily occupied during their negotiations. Only when a certain participant wins the bid as appointed by the administrator at last, resources of other participants can be released and used for bidding of other administrators. This may lead to a great waste of idle resources in the corresponding system, and also low negotiation efficiency in cases of different administrators and multiple tasks. A commit protocol of CNA can effectively improve system resource utilization. However, only one contract can be signed eventually. Under the circumstance that an unmanned platform is deemed as an optimal executor of multiple tasks and a contract is signed between a single task and this platform, other tasks cannot be executed in the best way. Hence, the buffer pool mechanism is introduced. It allows an unmanned platform to sign multiple contracts at the same time, and after it is authorized to execute a certain task, it still can submit bids and participate in other tasks. Finally, a task sequence of such a platform takes form and the platform begins to execute tasks in this sequence in order. As a result, the resources of participants can be utilized to the largest extent during bidding, and blind bidding of participants can also be controlled by virtue of a load balancing strategy.

A buffer pool enables unmanned platforms with stronger abilities to get multiple tasks allocated. Although a single task can be executed in an optimal manner by the corresponding unmanned platform, it fails to rapidly complete all other tasks piling up on this platform from the perspective of the entire system. Consequently, most unmanned platforms of this system become idle, which may lower system efficiency. In order to prevent unbalancing of system resources utilized, the size of the buffer pool should be restricted properly. To be specific, more tasks can be distributed to comparatively idle participants, making the tasks executed in a more balanced way and achieving load balancing throughout the system.

For the improved contract net algorithm based on buffer pool mechanism (BPM-CNA), its procedures are described as follows:

Step1: A collaborative task is created randomly.
Step2: An administrator distributes this task to all unmanned platforms and invites for bid.
Step3: Unmanned platforms begin to evaluate task requirements based on their own abilities; and if an unmanned platform satisfies these requirements and the number of its tasks is still below the upper limit of the corresponding buffer pool, the unmanned platform generates a tender including personal information (e.g., self-capability) and submits the tender to the administrator.
Step4: If the administrator does not receive any tender, this indicates that no unmanned platforms are competent for this task and the algorithm ends; otherwise, the administrator selects and authorizes an unmanned platform obtaining the highest evaluation score based on the tenders.
Step5: If the unmanned platform with the maximum evaluation score refuses to accept the authorization, it signifies a bidding failure and the administrator goes back to Step 2 to select another unmanned platform; but if the unmanned platform accepts the authorization, it needs to report relevant information back to the administrator.
Step6: After the administrator is informed that the unmanned platform agrees on the authorization, it reconfirms whether to conclude a contract with this platform or not; if not, submission of tender fails; otherwise, a contract can be signed between the administrator and the unmanned platform, and the task is included in the buffer pool of the platform.
Step7: The unmanned platform selects a task of the highest priority in the buffer pool and begins to execute it; if the platform fails to execute this task smoothly, it can act as a new administrator and go back to Step 2 to release the task again; otherwise, information of completing the task should be reported back to the administrator and the algorithm ends.

E. HYBRID IMPROVED CONTRACT NET ALGORITHM

Concerning defects of the original CNA, three improvements were made in sections 3.2-3.4 from different perspectives. In addition, a hybrid improved contract net algorithm (Hy-CNA) was designed in combination with the advantages of such three improvements that show diverse emphases. Here, the mental coefficient is used as one of the basic attributes of heterogeneous unmanned platforms. Real-time information of all unmanned platforms is also recorded in a blackboard to facilitate the administrator while selecting qualified participants for bidding. In the process of submission of tender, the buffer pool mechanism is adopted, so that the unmanned platform can accept multiple tasks. Moreover, these tasks should be allocated as balanced as possible, achieving load balancing throughout the system.

Procedures of the Hy-CNA are as follows:

Step1: The mental coefficient is initialized.
Step2:A collaborative task is created randomly.
Step3:An administrator constructs a blackboard to record information of various unmanned platforms; if the current task is the first task in the system, the initialized unmanned platform data are added in the blackboard; otherwise, the administrator distributing the task takes the responsibility to request information in the blackboard of the previous administrator.
Step4: The administrator begins to distribute the task to competent unmanned platforms according to their mental coefficients recorded in the blackboard, and calls for a bid.
Step5: Unmanned platforms begin to evaluate task requirements based on their own abilities; and if an unmanned platform satisfies these requirements and the number of its tasks is still below the upper limit of the corresponding buffer pool, the unmanned platform generates a tender including personal information (e.g., self-capability) and submits the tender to the administrator.
Step6: If the administrator does not receive any tender, this indicates that no unmanned platforms are competent for this task and the algorithm ends; otherwise, the administrator selects and authorizes an unmanned platform obtaining the highest evaluation score based on the tenders.
Step7: If the unmanned platform with the maximum evaluation score refuses to accept the authorization, it signifies a

bidding failure and the administrator goes back to Step 2 to select another unmanned platform; but if the unmanned platform accepts the authorization, it needs to report relevant information back to the administrator.

Step8: After the administrator is informed that the unmanned platform agrees on the authorization, it reconfirms whether to conclude a contract with this platform or not; if not, submission of tender fails; otherwise, a contract can be signed between the administrator and the unmanned platform, and the task is included in the buffer pool of the platform.

Step9: The unmanned platform selects a task of the highest priority in the buffer pool and begins to execute it; if the platform fails to execute this task smoothly, it can act as a new administrator, considering this task being a failure, updating the mental coefficient, reporting the updated information back to the blackboard and going back to Step 3 to release the task again; otherwise, the mental coefficient is updated and information of completing the task should be reported back to the administrator who then updates the unmanned platform information in the blackboard; and the algorithm ends.

IV. EXPERIMENTAL DESIGN, VALIDATION, AND ANALYSIS

According to the number of tasks and unmanned platforms, six sets of data were designed for the experiment. Respectively, the number of tasks was designed to be 30, 50, 80, 100, 120 or 150; and the total number of unmanned platforms was selected to be 30 or 90. On this basis, dynamic allocation of collaborative tasks was carried out on a multi-unmanned platform. Relevant results were comprehensively analyzed and compared. The specific settings are presented in TABLE 1 below:

TABLE 1. Data design.

Task serial number	Total number of tasks (regular/collaborative)	Number of UAV	Number of UGV	Number of unmanned airships
1	30（15/15）	10	10	10
2	50（25/25）	10	10	10
3	80（40/40）	10	10	10
4	100（50/50）	30	30	30
5	120（60/60）	30	30	30
6	150（75/75）	30	30	30

A. ALGORITHM PARAMETER DESIGN

For dynamic allocation problems of collaborative tasks on the multi-unmanned platform, their optimization objectives can be described at two aspects, that is, the maximum number of tasks completed in an unmanned platform system and the minimum energy consumption [11]. In other words, the weighted sum of time consumption, energy consumption and communication cost incurred by execution of the task reaches its smallest value. In terms of the corresponding computational formula, it can be obtained based on Equations (2.4), (2.5), (2.6), (2.7) and (2.8). Considering that the data here were designed comparatively at random, there are no requirements raised for weights of time and energy consumed. As for improvements proposed, they lay an emphasis on negotiation efficiency improvement. Therefore, the cost of communication is particularly important. In this case, their weights are designed as follows (please refer to TABLE 2).

TABLE 2. Weight settings for the objective function.

Parameter	Value
Total task time-consuming α	0.3
Total task energy-consuming β	0.3
Total task communication cost γ	0.4
Task completion tendency φ	0.5
task energy-consuming reduce tendency ω	0.5

Regarding MC-CNA, the parameter design involved in a mental coefficient may affect how the mental coefficient expresses attributes of the unmanned platform, further exerts an effect on the administrator's judgment and eventually influences task allocation outcomes. Through repeated experiments of parameter design and value setting, task allocation results with diverse parameter settings were analyzed and compared, identifying the parameter values for various mental coefficients used in this paper, as shown in TABLE 3 and 4.

TABLE 3. Credibility parameters of mental coefficients.

Parameter	Value
Reward coefficient for successful execution of the task δ	0.25
Penalty coefficient when task execution fails ε	0.4

TABLE 4. Risk tolerance parameters of mental coefficients.

Parameter	Value
Reward coefficient of risk tolerance when successful σ	0.3
Penalty coefficient of risk tolerance at the time of failure τ	0.3
Coefficient of change during the execution of the task θ	0.1

B. EXPERIMENTAL RESULTS

The six sets of data were used as input to run the algorithms. Relevant computational results are presented as follows:

In TABLE 5 and 6, no significant differences are identified in the number of tasks completed, the integrated assessment score and the time consumed between MC-CNA and CNA.

TABLE 5. Computational results based on CNA.

	Task serial No. Total number of tasks (regular/collaborative)	Number of tasks completed (regular/collaborative)	Integrated assessment score	Time consumed (s)	Number of times of communication
1	30 (15/15)	28 (14/14)	0.774193	4.2581	991
2	50 (25/25)	47 (24/23)	0.773478	5.6388	1657
3	80 (40/40)	73 (38/35)	0.757534	7.5246	2677
4	100 (50/50)	95 (47/48)	0.792725	10.5939	9949
5	120 (60/60)	116 (60/56)	0.835821	12.3614	10960
6	150 (75/75)	139 (72/67)	0.810065	15.0454	13754

TABLE 6. Computational results based on MC-CNA.

	Task serial No. Total number of tasks (regular/collaborative)	Number of tasks completed (regular/collaborative)	Integrated assessment score	Time consumed (s)	Number of times of communication
1	30 (15/15)	28 (14/14)	0.783913	4.0931	173
2	50 (25/25)	46 (24/22)	0.763886	5.5542	288
3	80 (40/40)	71 (37/34)	0.758123	7.3614	540
4	100 (50/50)	92 (47/45)	0.794857	10.7549	993
5	120 (60/60)	113 (58/55)	0.829721	11.9376	1179
6	150 (75/75)	135 (71/64)	0.808101	14.3683	1534

As improvements of MC-CNA are primarily targeted at the bidding phase of a contract net and aiming at perfecting broadcasting situations in this process, therefore, they place a major influence on the number of times of communication during implementation of CNA. In this consideration, the number of times of communication generated by MC-CNA was compared with that of CNA and relevant results are presented in FIGURE 1.

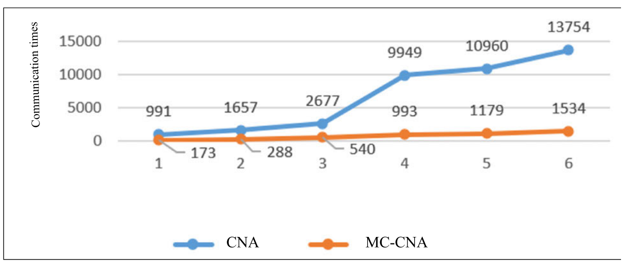

FIGURE 1. Comparison of communication times before and after MC-CNA improvement.

Clearly, MC-CNA effectively reduces the negotiation frequency of CNA. In terms of CNA, the administrator of each task needs to communicate with all participants at least once because broadcasting should be performed during an invitation for bid to seek an appropriate participant. Consequently, algorithm complexity for communication reaches $O(mn)$ as far as CNA is concerned. With regard to MC-CNA, it assists the administrator in narrowing the range of bidding by virtue of mental coefficients, substantially reducing unnecessary communication. As a result, algorithm complexity for communication based on MC-CNA is lowered to $O(m)$.

As shown in TABLE 7, likewise, no great differences are found in the number of tasks completed and the integrated assessment score between BM-CNA and CNA. In terms of the time consumption and the number of times of communication incurred by BM-CNA, they both decline to a certain extent if compared with those of CNA. On this basis, both the time consumed and the number of times of communication, as computational results of BM-CNA, were compared with those of CNA.

As shown in FIGUREs 2 and 3, the time consumed by BM-CNA is shorter than that of CNA. This embodies that BM-CNA, recording information of unmanned platforms with the help of a blackboard, can help an administrator rapidly specify an appropriate participant. Additionally, the number of times of communication generated by BM-CNA is also smaller than that of CNA. Although algorithm complexity is still proved to be $O(mn)$, the number of times of communication is lowered by about 1/3 as a whole. This shows that the negotiation efficiency of BM-CNA is improved to a certain degree.

According to TABLE 8, the time consumed by BPM-CNA and its number of times of communication are not significantly different from those of CNA. In terms of the number of tasks completed and the integrated assessment score of the former, they are greatly improved. In this context, a comparison of the number of tasks completed and the integrated assessment score was made between BPM-CNA and CNA.

In FIGUREs 4 and 5, it can be observed that BPM-CNA is featured with more tasks completed and higher integrated assessment scores if compared with those of CNA. This proves that, by establishing a buffer pool of tasks, BPM-CNA

TABLE 7. Computational results based on BM-CNA.

Task serial No.	Total number of tasks (regular/collaborative)	Number of tasks completed (regular/collaborative)	Integrated assessment score	Time consumed (s)	Number of times of communication
1	30 (15/15)	27 (14/13)	0.764128	3.6837	615
2	50 (25/25)	47 (24/23)	0.760870	4.2693	1209
3	80 (40/40)	72 (37/35)	0.770086	5.8434	2273
4	100 (50/50)	94 (47/47)	0.794778	8.3003	6091
5	120 (60/60)	114 (58/56)	0.825456	9.5356	7317
6	150 (75/75)	137 (71/66)	0.814596	10.9908	9974

TABLE 8. Computational results based on BPM-CNA.

Task serial No.	Total number of tasks (regular/collaborative)	Number of tasks completed (regular/collaborative)	Integrated assessment score	Time consumed (s)	Number of times of communication
1	30 (15/15)	30 (15/15)	0.869488	4.3898	1081
2	50 (25/25)	50 (25/25)	0.860228	5.7906	1793
3	80 (40/40)	78 (39/39)	0.871164	7.1324	3130
4	100 (50/50)	100 (50/50)	0.893758	11.1362	10813
5	120 (60/60)	119 (60/59)	0.904290	13.3257	11919
6	150 (75/75)	145 (74/71)	0.895494	16.4299	15938

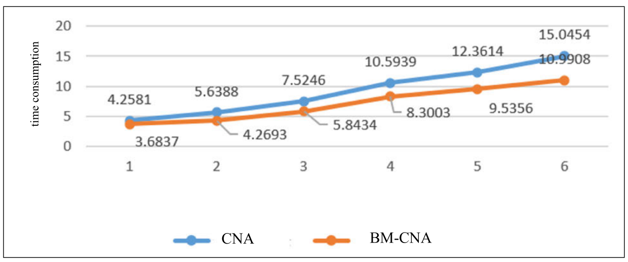

FIGURE 2. Comparison of time consumed by BM-CNA and CAN.

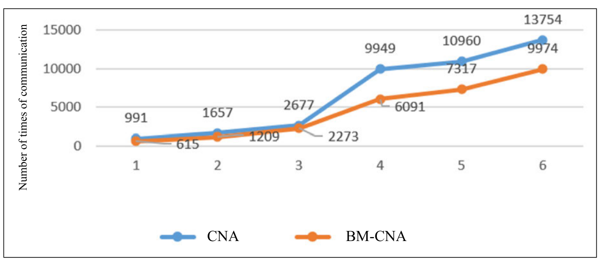

FIGURE 3. Comparison of the number of times of communication between BM-CNA and CNA.

has the ability to allocate tasks to an optimal executor to the greatest extent. In this way, it not only boosts the task completion rate, but also guarantees both validity and accuracy of task allocation schemes, improving the overall system efficiency.

Based on TABLE 9, in comparison with CNA, both the number of tasks completed and the integrated assessment score of Hy-CNA are significantly improved, while the time

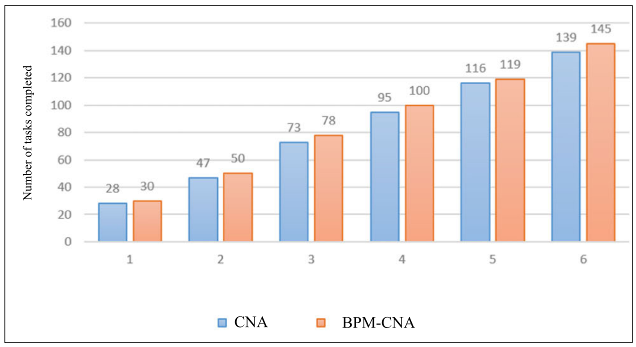

FIGURE 4. Comparison of the number of tasks completed between BPM-CNA and CAN.

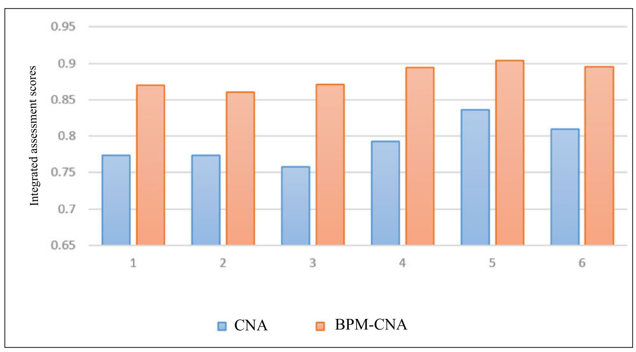

FIGURE 5. Comparison of the integrated assessment scores between BPM-CNA and CAN.

consumed and the number of times of communication significantly drop according to Hy-CNA. Hence, computational results of Hy-CNA are comprehensively compared with those

TABLE 9. Computational results based on HY-CNA.

Task serial No.	Total number of tasks (regular/collaborative)	Number of tasks completed (regular/collaborative)	Integrated assessment score	Time consumed (s)	Number of times of communication
1	30 (15/15)	30 (15/15)	0.905251	3.8584	195
2	50 (25/25)	49 (25/24)	0.893785	4.9417	304
3	80 (40/40)	77 (39/38)	0.893415	6.6024	579
4	100 (50/50)	99 (50/50)	0.945816	10.1531	1083
5	120 (60/60)	117 (60/57)	0.937694	11.2105	1321
6	150 (75/75)	143 (73/70)	0.932742	13.8539	1664

of CNA. For the purpose of making these results more visual, computational results of the above three improved algorithms were also considered and compared.

As can be observed from FIGUREs 6 to 9, no significant differences exist in the number of tasks completed and the integrated assessment score among MC-CNA, BM-CNA and CNA. In terms of BPM-CNA and Hy-CNA, their performance in the number of tasks completed and integrated assessment scores is superior to that of CNA; more specifically, the integrated assessment score is improved by 12%. The time consumed by BM-CNA is shorter than that of other algorithms; and it also reduces by 20% when the number of tasks reaches 180. Regarding the time consumption of other

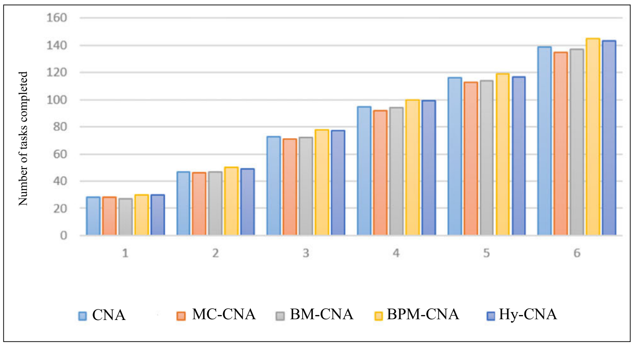

FIGURE 6. Comparison of the number of tasks completed before/after improvement.

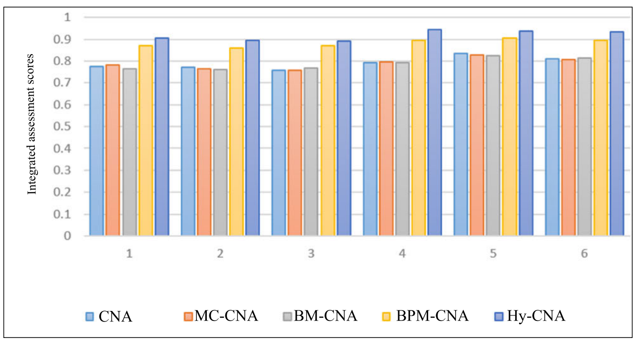

FIGURE 7. Comparison of integrated assessment scores before/after improvement.

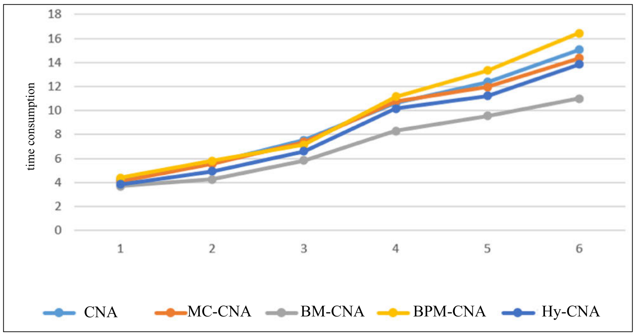

FIGURE 8. Comparison of time consumption before/after improvement.

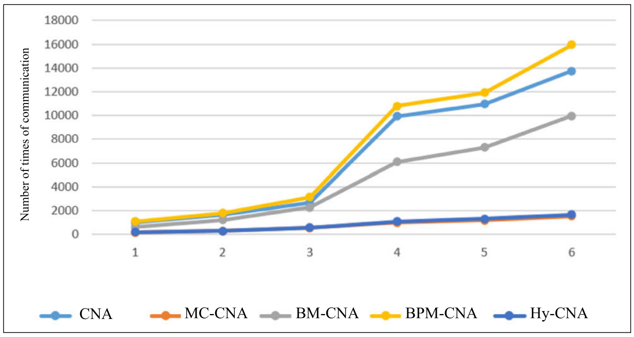

FIGURE 9. Comparison of the number of times of communication before/after improvement.

algorithms, no significant differences are found. Moreover, in comparison with CNA, BPM-CNA produces a slightly greater number of times of communication. For BM-CNA, its number of times of communication is lowered by 35%. Furthermore, the number of times of communication of both MC-CNA and Hy-CNA all show a substantial drop, forming a linear growth relationship only with the number of tasks.

V. CONCLUSION

Through data comparison based on the above experimental results, three improved CNAs and the Hy-CNA presented all play a positive role in improving the number of tasks completed and reducing the negotiation frequency. With the number of tasks and unmanned platforms changing, they can all solve relevant problems stably. Therefore, such four improved algorithms are both feasible and valid for the dynamic allocation of collaborative tasks on the multi-unmanned platform. Compared with CNA, BPM-CNA performs better in the number of tasks completed and the integrated assessment score, achieving a higher number of tasks completed and evaluation score. In both respects discussed above, MC-CNA and BM-CNA are less effective, and changes caused by such two improved algorithms are insignificant. The integrated assessment scores of all task allocation schemes can be ranked as: Hy-CNA>BPM-CNA>CNA=MC-CNA=BM-CNA. With regard to the BM-CNA, it is capable of effectively enhancing negotiation efficiency; for this reason, the time consumed is shorter than that of the other three algorithms. As for BPM-CNA, one more round of confirmation is required due to the existing commit protocol. Consequently, its negotiation efficiency is lower than that of CNA. In ascending order, these algorithms can be ranked as follows according to their time consumption: BM-CNA<Hy-CNA<MC-CNA<CNA<BPM-CNA. A mental coefficient is able to significantly reduce the number of times of communication, bringing complexity from $O(mn)$ down to $O(m)$. By boosting the negotiation efficiency, BM-CNA has the capability to lower the number of times of communication as well. However, its effectiveness is not as significant as that of MC-CNA. In accordance with the number of times of communication, these algorithms are ranked as: MC-CNA<Hy-CNA<BM-CNA<CNA<BPM-CNA.

This study profoundly investigated the dynamic allocation problems of collaborative tasks based on the multi-unmanned platform. On this basis, a dynamic collaborative task allocation model was established for dynamic collaborative task allocation problems of the heterogeneous unmanned platforms. In addition, a hybrid improved CNA was adopted to fulfill the dynamic allocation of collaborative tasks on a multi-unmanned platform. Furthermore, six sets of experimental data were designed to validate the algorithms and perform relevant comparative analysis. Thus, the proposed dynamic collaborative task allocation model based on the multi-unmanned platform is proved to be valid. It is also proved that improved algorithms presented in this study are effective in settling dynamic allocation problems of collaborative tasks on the multi-unmanned platform. Regardless of different action ranges, three improved algorithms of CNA were all able to effectively improve system efficiency. Considering this, the improved algorithms should be combined together to produce a hybrid improved CNA, that is Hy-CNA. Although the performance of Hy-CNA is just below that of a single improved algorithm in their time consumption and the number of times of communication, in the context of an extremely small number of times of communication, it can slightly improve the solving speed and present an optimal solution to task allocation schemes. Therefore, Hy-CNA satisfies the requirements of solving dynamic collaborative task allocation problems on the multi-unmanned platform.

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MAN ZHAO engaged in artificial intelligence teaching. She is currently an Associate Professor with the School of Computer Science, China University of Geosciences (Wuhan). In recent years, she has mainly participated in research on resource scheduling problems, such as satellite task planning and ocean observation task planning. Her current research interest includes application of intelligent optimization algorithms in engineering.

DONGCHENG LI (Member, IEEE) received the B.S. degree in computer science from the University of Illinois at Springfield and the M.S. degree in software engineering from The University of Texas at Dallas, where he is currently pursuing the Ph.D. degree. His research interests include search-based software testing, evolutionary computing, and machine learning.