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Multi-agent task allocation method based on the cost-effectiveness maximization multi-round auction algorithm

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Multi-agent task allocation plays a crucial role in achieving efficient collaboration in heterogeneous multi-agent systems, especially in complex and dynamic environments. However, existing auction-based task allocation approaches often focus primarily on economic optimization or bid-oriented allocation while insufficiently considering the compatibility between agent capabilities and task attribute requirements, along with the overall cost-effectiveness from the task owner's perspective. To address these limitations, in this paper, we propose a task allocation framework, which integrates task fitness modeling with cost-effectiveness maximization, and further develop a distributed multi-round auction mechanism. In particular, a task fitness model is constructed to quantitatively evaluate the suitability of agents for different tasks by combining multiple capability dimensions, where the importance of different task attributes is determined using the analytic hierarchy process (AHP). Based on this, a cost-effectiveness metric is defined by jointly considering agent bids and task fitness, and a multi-round auction algorithm, with dynamic bidding and an improved payment rule, is designed to maximize the overall task cost-effectiveness while ensuring incentive compatibility and individual rationality. Extensive simulation results demonstrate that the proposed approach significantly improves task cost-effectiveness and maintains high task execution suitability compared with conventional first-price, second-price, and existing multi-round auction mechanisms.

KEYWORDS

task allocation, multi-agent, auction game, task fitness, task cost-effectiveness

1 Introduction

With the rapid development of artificial intelligence and Internet of Things (IoT) technologies [1–5], traditional single-agent systems are gradually exposing structural limitations when dealing with complex, multi-constrained, and highly dynamic uncertain tasks. These limitations are reflected not only in restricted environmental perception capability and limited information-processing bandwidth but also in a lack of sufficient flexibility and adaptability in task execution, resource allocation, and strategy adjustment. Although performance can be improved by continuously enhancing the hardware computing capability of a single agent or optimizing its isolated decision-making model, such an approach is difficult to keep pace with the exponential growth in task scale, complexity, and real-time requirements in practical scenarios. Meanwhile, it inevitably leads to diminishing marginal benefits, significantly increased system development costs, and heavier life cycle maintenance burdens. For example, in IoT environments [6–8], the large number of heterogeneous devices, dynamically evolving network topologies, and highly concurrent low-latency tasks further exacerbate the inherent limitations of single-agent systems. Therefore, single-agent architectures are increasingly unable to serve as an ideal solution in many mission-critical application environments.

Compared with single-agent systems, multi-agent systems leverage collaborative sensing, cooperative decision-making, and coordinated execution among multiple agents, thereby exhibiting superior robustness, flexibility, and scalability under resource constraints, environmental uncertainties, and high-task concurrency conditions. By enabling reasonable task-level cooperation, fully exploiting the complementary advantages of heterogeneous agents at the capability level, and ultimately enhancing overall system efficiency at the global level, multi-agent systems provide an effective new paradigm for intelligent execution in complex task scenarios [9, 10].

A multi-agent system is a complex system composed of multiple agents working together [11]. In such systems, multiple tasks typically coexist, and agents must collaborate to complete them so as to achieve the overall system objectives. Therefore, task allocation, as the logical starting point and core component for realizing efficient cooperation, has become an inevitable and critical issue in MAS research. The objective of task allocation is to optimize task execution performance or system utility, such as maximizing the number of successfully completed tasks or minimizing execution time and resource consumption [12]. In addition to optimization objectives, a large number of constraints must also be satisfied during the task allocation process. For example, due to differences in configuration, performance, workload, and functionality, different types of agents may only be capable of executing specific categories of tasks. Moreover, in complex multi-agent system scenarios, significant heterogeneity exists among agents in terms of functionality, perception, and decision-making capabilities. How to efficiently and cooperatively assign these agents to diverse and dynamic tasks thus becomes a highly challenging research problem. This challenge not only involves accurate modeling of individual agent capabilities and precise interpretation of task requirements but also requires achieving an optimal balance among real-time collaboration, resource constraints, and overall system effectiveness.

Research on auction algorithms for solving task allocation problems has received widespread attention from scholars in recent years. In 2002, Zlot et al. proposed an auction mechanism that utilizes a market architecture to maximize returns and can adapt to the dynamic joining and exiting of team members [13]. The auction-based task allocation algorithm proposed by Melvin et al. (2007) [14] is suitable for scenarios in which multi-agent systems operate in two-dimensional terrain and tasks have assigned priorities and nonoverlapping time windows. In 2009, Choi et al. first proposed the consensus-based auction algorithm (CBAA) and the consensus-based bundling algorithm (CBBA) [15], drawing on the principles of market mechanisms and applying them to distributed task allocation mechanisms. When conflicts arise, consensus communication based on local communication is introduced to solve them. In the CBAA algorithm, both buyers and sellers submit bids at the same time, and the system determines the transaction price based on the bids of the buyers and sellers, thereby achieving transactions between the buyers and sellers. The characteristic of the CBAA algorithm is that the trading process is continuous and can repeatedly submit bids until the transaction is reached. The CBBA is an algorithm based on the market auction mechanism, in which each agent formulates its own bidding strategy based on its own abilities and task requirements, and then sends the bidding results to other agents for comparison and negotiation. During the negotiation process, agents use consensus algorithms to determine the final task allocation result. In 2010, Mercker et al. proposed a decentralized extended CBBA (ECBBA) [16] to solve multi-objective and multi-task allocation problems for unmanned vehicles, and this algorithm allows the addition of local "pop up" targets and re-convergence to the solution without solving the entire optimization problem. In 2011, Liu et al. proposed the contract business expansion-based contract network [17] based on a concurrent transaction mechanism, which enables the rapid implementation of task allocation, reduces the network communication overhead between agents, and maximizes the efficiency of multi-agent system cooperation and the overall performance of the system. In 2011, Jones et al. proposed an auction algorithm based on double-layer auction to solve the multi-agent task allocation problem under path constraints [18]. In 2012, Jia et al. developed a distributed auction on a two-level network using the UQ-PSP auction algorithm [19] to achieve effective resource allocation for maximizing social welfare. In 2013, Ying established a collaborative task allocation model of a multi-agent system based on the contract net protocol (CNP) [20].

In 2015, Lee et al. proposed a distributed auction algorithm, RODAA [21], which allocates tasks through an auction mechanism to improve the resource utilization efficiency of robots. In 2015, Das et al. proposed the consensus-based parallel auction and execution (CBPAE) algorithm [22], which is a distributed algorithm based on auction and consensus principles for task allocation in multiple heterogeneous autonomous robot systems deployed in medical institutions. In 2015, Parker et al. proposed a distributed algorithm based on maximum sum [23], which is suitable for allocating tasks where the cost of completing tasks increases over time for agents. Inspired by the models used by bounty hunters and bail guarantors, Wicke et al. proposed a multi-agent task allocation system similar to auctions in 2015 [24]. In 2016, Cheng et al. proposed an auction algorithm for multilayer cost calculation [25], which divides cost calculation into four layers based on four types of constraints to better solve the problem of dynamic task allocation for unmanned aerial vehicles. In 2018, Fu et al. conducted a study on the task allocation problem of multiple unmanned aerial vehicles and considered the limited communication bandwidth during the research process, optimizing the task allocation [26]. Based on the CBBA, the task list is modified by copying collaborative tasks, and a judgment mechanism is added to ensure the uniqueness of repetitive task allocation so as to achieve the goal of assigning multiple drones to the same task. The algorithm performance is improved by using bidding distortion links, and the CBBA is applied in asynchronous environments to reduce communication burden. In 2019, Zheng et al. studied the application of the CBBA in task allocation in the scenario of unmanned aerial vehicle returning to the takeoff base after completing a task [27] and improved the CBBA by proposing a closed-loop CBBA to allocate tasks closer to the direction of the drone's takeoff base. In 2020, Otte proposed an auction algorithm to solve the multi-agent task allocation problem in unstable communication scenarios [28]. The existing studies on task allocation primarily focus on economic benefit optimization or cost minimization. However, they still exhibit limitations in modeling task attribute constraints and in capturing the capability–task matching relationship. As a result, the obtained allocation outcomes may be optimal only in the economic sense while lacking sufficient task execution quality, or insufficient capability matching may lead to increased execution risks.

In this paper, we address the task allocation problem in multi-agent systems and propose a multi-round auction-based task allocation framework that integrates task fitness modeling with the concept of cost-effectiveness maximization. A task allocation algorithm that explicitly accounts for agent capability characteristics is designed accordingly. First, the concept of task fitness is introduced to represent the adaptability of an agent to multiple task attributes. Second, based on task characteristics, the analytic hierarchy process (AHP) is used to determine the relative importance weights of task attributes in the proposed task fitness function. The task value, agent cost, agent efficiency, task fitness, and the task allocation problem are jointly modeled. Then, the cost-effectiveness provided by an agent for a task is defined as the weighted sum of the agent's bid and its fitness to the task. Finally, by designing buyer matching rules, payment rules, and a dynamic bidding strategy, a distributed multi-round auction algorithm is developed with the objective of maximizing task cost-effectiveness, thereby achieving optimal task allocation.

The main contributions of this paper are summarized as follows: (1) a task fitness modeling framework that integrates task attributes and agent capability characteristics is proposed. By using the AHP to quantify the importance of task attributes, the proposed framework enhances the accuracy of capability–task matching in task allocation decision-making. (2) From the perspective of the task owner, the concept of task cost-effectiveness is introduced, and a joint optimization objective that simultaneously considers economic returns and execution performance is formulated. Furthermore, a distributed multi-round auction algorithm (FMMRA) is designed, which incorporates a dynamic bidding mechanism and an improved payment rule to ensure incentive compatibility and individual rationality of the auction mechanism. (3) Comprehensive theoretical analysis and simulation experiments are conducted to validate the superiority of the proposed algorithm, demonstrating significant improvements particularly in task cost-effectiveness and overall system performance.

2 Multi-agent multi-task fitness

2.1 Task fitness definition

In scenarios where multiple agents perform multiple tasks, different agents exhibit different performance in terms of computing resources, mobility capabilities, decision-making capabilities, and firepower allocation. For example, for the characteristics of the target to be captured in an encirclement-type task, if it is a stationary target that does not have the ability to resist force, the agent executing the encirclement task for that target requires lower mobility and firepower requirements. If it is a stationary target with the ability to resist force, it requires high maneuverability and firepower equipment. If it is a moving target that does not have the ability to resist with force, the requirements for maneuverability and decision-making ability are high. If it has the ability to resist with force, higher requirements for firepower equipment are necessary to ensure suitability for carrying out the encirclement mission against the target. Therefore, it is important to allocate tasks based on the characteristics of the task and the different ability attributes of the agent before actual task execution, which is conducive to maximizing the expected completion effect of the task.

Multi-agent task allocation needs to consider the adaptability of different agents to different tasks. Therefore, in this paper, we introduce the concept of task fitness to represent the comprehensive adaptability of agents to all attributes of a task when performing a task. An effective fitness function is designed to calculate the fitness of the agent to the task.

The modeling process of fitness function is as follows, and the agent set is presented in Equation 1:

$$A = \{A_1, \ldots, A_i, \ldots, A_N\}, i \in N. \tag{1}$$

The attribute set A_i^{para} of the agent is presented in Equation 2:

$$A_i^{para} = A_i^{val}, A_i^{comp}, A_i^{move}, A_i^{dec}, A_i^{def}, A_i^{fight}, \tag{2}$$

where A_i^{para} represents the abstract representation of the value measurement of the agent, A_i^{comp} represents the abstract representation of the computing power of the agent, A_i^{move} represents the abstract representation of the mobility ability of the agent, A_i^{dec} represents the abstract representation of the decision-making ability of the agent, A_i^{def} represents the abstract representation of the defense ability of the agent, and A_i^{fight}represents the abstract representation of the firepower equipment of the agent.

The task set is defined as shown in Equation 3:

$$T = \{T_1, \ldots, T_j, \ldots, T_N\}, j \in M. \tag{3}$$

The attribute set T_j^{para} of the task is presented in Equation 4:

$$T_j^{para} = T_j^{val}, T_j^{comp}, T_j^{move}, T_j^{dec}, T_j^{def}, T_j^{fight}, \tag{4}$$

where T_j^{val} represents an abstract representation of the reward for completing the task, T_j^{comp} represents an abstract representation of the computing power required for the task, T_j^{move} represents an abstract representation of the mobility capability required for the task, T_j^{dec} represents an abstract representation of the decision-making capability required for the task, T_j^{def} represents an abstract representation of the defense capability required for the task, and T_j^{fight} represents an abstract representation of the firepower equipment required for the task. The fitness function of agents to tasks can be expressed as shown in Equation 5:

$$F_{ij} = \sum_{\beta=1}^{\alpha} \lambda_\beta^j f_\beta^{ij}, \tag{5}$$

where λ_β^j represents the importance weight coefficient of the β-th attribute of task j, which mainly represents the importance of different attributes to the task. f_β^{ij} represents the fitness value of agent i to the β-th attribute of task j, which is mainly obtained based on statistical laws.

In the task allocation process, tasks, attributes, and agents form an interrelated decision system. Each task possesses certain attributes, such as required resources, requirements for capabilities. Agents are the subjects that perform tasks with different capabilities, resources, location states, and preferences. The task attributes determine the conditions required to complete the task, and the agent determines whether it has the capabilities and advantages to complete the task based on the task attributes. Therefore, to ensure that the agents perform the task efficiently, it is necessary to consider the relationship between task attributes and agents, carry out reasonable and effective collaborative task planning, fully utilize the advantages of each agent, and maximize the benefit of the overall task allocation.

To sum up, the calculation of task fitness first needs to make a preliminary selection according to the agent attributes and task attributes. The screening rule is that the agent can perform subsequent fitness calculation only when it meets at least the minimum requirements of the task. Second, according to the importance of different attributes to the task, complete the design of attribute weight coefficient, set the fitness value of agent i to the β-th attribute of task j according to the statistical law, and finally complete the calculation of fitness according to the formula. For a clear understanding of notations in this paper, their detailed descriptions are provided in Table 1.

TABLE 1 Description of key notations.

Notation	Description
A	Agent set
A^{para}	Agent attribute set
T	Task set
T^{para}	Task attribute set
F	Fitness function
λ_β^j	Importance weight coefficient of the β-th attribute of task j
f_β^{ij}	The fitness value of agent i to the β-th attribute of task j
G	Judgment matrix
CI	Consistency ratio
CR	Random consistency ratio
W	Maximum feature vector
X	Task allocation matrix
R	Task benefit

2.2 Construction of the fitness function

We determine the weight coefficient of each attribute in the task fitness evaluation system based on the AHP. From the perspective of the evaluation system, the AHP performs fine-grained decomposition of the evaluation system according to the target layer, criterion layer, and indicator layer. First, the importance of each attribute of the task is distinguished based on expert ratings, and a judgment matrix is constructed based on the importance coefficient. Second, it is determined whether the weights of expert evaluation indicators meet the consistency testing criteria. Finally, based on this judgment matrix, the maximum feature vector and the weight coefficients of each attribute of the task are calculated. The specific steps are as follows.

2.2.1 Construction of a judgment matrix

According to the task fitness evaluation system, the corresponding indicator evaluation judgment matrix is constructed. In the construction of the judgment matrix, a bottom-up approach is adopted. First, it is necessary to construct a judgment matrix for the indicator layer. After obtaining its evaluation weights, the weights of other levels are determined layer by layer, and the final evaluation result of the target layer is the terminal evaluation level. Among them, the establishment of the judgment matrix relies on the "1-9" index importance coefficient method.

We construct a three-layer model for fitness evaluation. The first layer is the task layer, representing different tasks, and the second layer is the criteria layer, which mainly includes computing ability, mobility ability, decision-making ability, defense ability, and firepower allocation. The third layer consists of multiple agents executing tasks. As shown in Equation 6, G is the construction form of the α-order judgment matrix.

$$G = \begin{bmatrix} G_{11} & \cdots & G_{1\alpha} \\ \vdots & \cdots & \vdots \\ G_{\alpha 1} & \cdots & G_{\alpha\alpha} \end{bmatrix}, \tag{6}$$

where α is the order of the matrix, representing that the second layer has α attributes. G_{ij} represents the relative importance index of the i-th attribute relative to the j-th attribute.

2.2.2 Matrix test

The attribute weights obtained using the AHP need to undergo matrix testing to determine whether the importance coefficients between attributes are reasonable. The essence of matrix testing is to determine the size of the random consistency ratio, and if the ratio value is less than 0.1, then the matrix is considered reasonable. The calculation formulae for the consistency ratio CI and the random consistency ratio CR are presented in Equations 7, 8, respectively:

$$CI = \frac{\lambda_{max} - \alpha}{\alpha - 1}, \tag{7}$$

$$CR = \frac{CI}{RI} = \frac{\lambda_{max} - \alpha}{(\alpha - 1)\, RI}, \tag{8}$$

where λ_{max} is the maximum eigenvalue of the judgment matrix G and RI is the average random consistency indicator.

2.2.3 Attribute weight coefficients

Attribute weight coefficients are calculated based on the judgment matrix. The eigenvalues and eigenvectors of the judgment matrix G are calculated, and the normalized eigenvectors corresponding to λ_{max} are the weight coefficients of each attribute. After the judgment matrix is verified to be reasonable, the importance weight of the lower α elements in the adjacent two layers of the structure to a certain element in the upper layer can be calculated, represented by the maximum feature vector W corresponding to the maximum feature root λ_{max} of the judgment matrix G, as shown in Equation 9:

$$G \bullet W = \lambda_{max} \bullet W, \tag{9}$$

The feature vector W corresponding to the maximum eigenvalue is the importance weight vector of the lower layer α elements in the adjacent two layer structure to a certain upper layer element, which is the attribute weight coefficient. The importance weight coefficients of the α attributes of task j are expressed as $W = \left[\lambda_1^j, \lambda_2^j, \ldots, \lambda_\alpha^j\right]$, indicating that the importance weight coefficients λ_β^j of task j for the β-th attribute have been calculated.

According to the formula of the fitness function, it is necessary to further calculate f_β^{ij}, that is, the fitness value p_{beta}^j of the agent to the β-th attribute of the task. The determination of f_β^{ij} is based on the actual relationship between the agent and the task.

3 Construction of the multi-agent task allocation model

The auction algorithm is a commonly used method to solve the optimal task allocation problem of multi-agent systems. In this study, the agent is the buyer, the task holder is the seller, and the task is the product. The task holder has the power to allocate tasks, and the agent bids competitively to obtain the task. Executing the task results in a reward for the task while also paying a certain cost. The ultimate benefit of the agent is the task reward minus the bid and cost, and the economic benefit of the task holder is the agent's bid. This process involves using auction algorithms to solve multi-agent task allocation problems.

3.1 Construction of the efficiency function

An agent can only execute one task, and a task can be assigned to multiple agents for collaborative execution. Due to the different measurement of various attribute abilities possessed by different agents and the different requirements of different tasks, it is important to allocate tasks reasonably to improve the expected effect of task completion. The task allocation matrix is defined in Equation 10:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1M} \\ \vdots & \cdots & \vdots \\ x_{N1} & \cdots & x_{NM} \end{bmatrix}, \tag{10}$$

where $x_{ij} = 0$ indicates that task j is not assigned to agent i for execution and $x_{ij} = 1$ indicates that task j is assigned to agent i for execution.

In the auction algorithm, the seller announces product information to the auctioneer. In this study, to publish task information, the auctioneer broadcasts the information to the buyer, and the buyer bids based on task information. In addition, the task is for the product, the buyer is the agent, and the task is assigned to the agent that successfully bids for the task; the seller is the task holder and has the power to assign tasks to designated agents. We define the cost-effectiveness of the agent task as the weighted sum of the fitness of the agent to the task and the final bid of the agent to the task, along with the cost-effectiveness of the task as the sum of the cost-effectiveness of all agents performing the task. Using task cost-effectiveness as the main indicator to evaluate the effectiveness of task allocation, an efficiency function is established based on this.

3.2 Task benefit function

The benefits of agent i in completing task j depend on the strategic value T_j^{val} of target task j. Task benefits and the cost of executing the task determine the expected profit of the agent in executing the task. The agent prioritizes selecting tasks with high expected profits for bidding, aiming to obtain the qualification to execute the task that better aligns with actual needs and facilitate the optimal allocation of tasks. The calculation formula for the benefit R_{ij} of executing task j for agent i is presented in Equation 11:

$$R_{ij} = T_j^{val}. \tag{11}$$

3.3 Task cost function

The cost factors that agent i needs to pay for executing task j mainly include path cost and agent value measurement. The path cost depends on the straight-line distance L_{ij} between the agent i and the target location of task j, along with the fuel consumption Oil_i per unit distance traveled by the agent. Different agents L_{ij} and Oil_i are different, and the smaller the path cost, the lower the fuel consumption of the agent in executing the task. Therefore, priority is given to assigning targets with lower path costs to the agent, enabling the task to be completed with minimal fuel consumption. The path cost function is represented in Equation 12:

$$Path_{ij} = \frac{L_{ij} Oil_i}{max\left(L_{1j} Oil_1, L_{2j} Oil_2, \ldots, L_{Nj} Oil_N\right)}, \tag{12}$$

where $max(L_{1j}, L_{2j}, \ldots, L_{Nj})$ represents the maximum linear distance from all agents to the target location of task j. Agents with different value measures A_i^{val} have different self-losses when flying the same distance, such as expensive agents flying a specified distance, which results in higher loss costs. Therefore, A_i^{val} is introduced into the calculation of task cost function $Cost_{ij}$, as represented in Equation 13:

$$Cost_{ij} = A_i^{val} \cdot Path_{ij}. \tag{13}$$

3.4 Agent efficiency function and task fitness function

Agent efficiency function is expressed in Equation 14:

$$U_{ij} = x_{ij} \cdot \left(R_{ij} - Cost_{ij}\right). \tag{14}$$

The efficiency function of the agent characterizes the expected profit of the agent i in executing task j. The agent prioritizes the execution of tasks with high expected profit to maximize its own profits.

The fitness function F_{ij} of agent i to task j is expressed in Equation 15:

$$F_{ij} = \sum_{\beta=1}^{\alpha} \lambda_{\beta}^{j} f_{\beta}^{ij}, \tag{15}$$

where λ_{β}^{j} represents the gain coefficient of the β-th attribute of task j, mainly representing the importance of different attributes to the task, f_{β}^{ij} represents the fitness value of agent i to the β-th attribute p_{β}^{j} of task j, and f_{β}^{ij} mainly obtains corresponding data based on statistical laws.

In summary, based on the constructed agent efficiency function and task fitness function, the utility evaluation in this work is explicitly designed as a comprehensive assessment process that couples multidimensional agent capability characteristics with task attribute requirements. This enables the framework to consider not only whether an agent has the motivation to participate in competition but also its execution suitability and efficiency for specific tasks. Meanwhile, by incorporating an AHP-based attribute weighting mechanism, the task fitness function can dynamically characterize the importance of different capability dimensions in varying task scenarios, rather than assuming homogeneous or equally weighted task attributes. With this capability-aware utility modeling approach, the system can achieve more discriminative performance evaluation, effectively avoiding allocation results that are purely economically optimal but neglect execution quality, thereby providing a more reliable utility foundation for subsequent task allocation decisions.

3.5 Modeling task allocation problems

Based on the task efficiency function, the agent conducts bidding on tasks in the task set. To meet the actual task requirements, the constraint conditions are defined as follows.

A single agent can only be assigned responsibility for completing one task, which meets the requirements shown in Equation 16:

$$\sum_{j=1}^{M} x_{ij} = 1. \tag{16}$$

The various capability metrics of an agent, such as computing power, mobility, decision-making power, defensive power, and firepower allocation, must be greater than the required capability metrics for the task to be executed. The constraints are presented in Equations 17–21:

$$A_j^{comp} > T_j^{comp}, \tag{17}$$

$$A_j^{move} > T_j^{move}, \tag{18}$$

$$A_j^{dec} > T_j^{dec}, \tag{19}$$

$$A_j^{def} > T_j^{def}, \tag{20}$$

$$A_j^{fight} > T_j^{fight}, \tag{21}$$

All tasks are executed by at least one agent, which meets the requirements presented in Equation 22:

$$\sum_{i=1}^{N} x_{ij} \geq 1. \tag{22}$$

Task allocation is directed toward maximizing overall task cost-effectiveness, as shown in Equation 23:

$$F(X) = max \sum_{i=1}^{N}\sum_{j=1}^{M} \zeta_{ij} = max \sum_{i=1}^{N}\sum_{j=1}^{M} \left(w_1 b_{ij} + w_2 F_{ij}\right), \tag{23}$$

where ζ_{ij} is the cost-effectiveness of the agent, b_{ij} is the bid of agent i for task j, F_{ij} is the fitness of agent i for task j, w_1 and w_2 are the corresponding weight coefficients, and $F(X)$ is the cost-effectiveness of task. The higher the cost-effectiveness of the task, the better the overall performance of the bid received by the agent and the completion effect of the task by the task holder.

It can be observed that in formulating the task allocation problem, this study no longer adopts the traditional paradigm dominated solely by task rewards or bidding factors. Instead, the problem framework is reconstructed from a comprehensive perspective that couples capability matching, task attributes, and economic incentives. In particular, multidimensional agent capability characteristics, task attribute requirements, and the task fitness evaluation mechanism are explicitly incorporated into the problem description, and a cost-effectiveness metric oriented toward the task owner's benefit is further introduced. This modeling framework not only captures the compatibility relationship between heterogeneous agents and multi-attribute tasks but also establishes an effective balance between incentive-driven economic objectives and guaranteed task execution quality.

4 Distributed multi-round auction algorithm based on maximizing task cost-effectiveness

Bidding strategy, buyer matching, and payment rules are important processes in auction mechanisms, among which the bidding strategy mainly solves the problem of how buyers can bid to obtain the desired goods. In this study, this is reflected in the problem of how agents can bid to improve the probability of successful bidding and secure tasks with high expected profits. Buyer matching mainly solves the problem of which buyer is more suitable for the seller, which is reflected in this study as the problem of which agent is more suitable for executing tasks. Payment rules refer to the pricing rules for the final transaction price paid by the buyer to the seller. The above three processes in the distributed multi-round auction algorithm based on maximizing cost-effectiveness proposed in this study are designed in sequence.

4.1 Bidding strategy

Before determining which seller to bid for, we need to calculate the expected profit γ_{ij} of seller j on buyer i. The formula γ_{ij} is expressed in Equation 24:

$$\gamma_{ij} = R_{ij} - Cost_{ij}. \tag{24}$$

A first-round auction process is designed, in which the bid b_{ij} is set to half of the expected profit γ_{ij}, as shown in Equation 25:

$$b_{ij} = \frac{1}{2}\gamma_{ij} = \frac{1}{2}\left(R_{ij} - Cost_{ij}\right). \tag{25}$$

The expected final profit $epro_{ij}$ is presented in Equation 26:

$$epro_{ij} = \gamma_{ij} - b_{ij}. \tag{26}$$

The bidding strategy involves the buyer selecting the seller with the highest expected final profit $epro_{ij}$ from all sellers to bid, which is beneficial for the buyer's economic benefits. If buyer i fails to compete with auctioneer j in this round, then the bid b_{ij} of auctioneer j is adjusted in the next round by increasing it appropriately [29], and the actual profit is reduced to improve the likelihood of winning the bid. The updated formula for bid b_{ij} is presented in Equation 27:

$$b_{ij} = b_{ij} + \xi b_{ij}. \tag{27}$$

In summary, this process identifies two issues: first, which product is more suitable for the buyer, and second, how the buyer can bid to obtain the product. In this study, these correspond to determining which task is more suitable for the agent and how the agent adjusts its bid to secure the task. To maximize the cost-effectiveness of tasks, it is necessary to design a buyer matching algorithm that reversely selects the most suitable agent (buyer) from the perspective of the task holder (seller).

4.2 Buyer matching

When using auction algorithms to solve task allocation problems, buyer matching refers to the process in which the task holder selects the best agent from multiple bidding agents for the task based on a certain metric and assigns the task to the agent. The buyer matching stage is a very important part of auction algorithms, which directly affects the seller's efficiency. Therefore, when designing auction algorithms, it is necessary to fully consider the strategies and rules for buyer matching. In this study, according to the weighted sum of agent i's bid b_{ij} and fitness for task j, the task holder considers not only the price but also the fitness of agent i for its own task j when selecting an agent. The cost-effectiveness ζ_{ij} of the agent is defined in Equation 28. The higher the ζ_{ij}, the greater the comprehensive cost-effectiveness of task j assigned to agent i in terms of economic benefits (agent bid) and task completion effects (task fitness), indicating that the task is more suitable for assignment to the agent. While ensuring benefits, it is also more advantageous for task j to complete as task j has a stronger willingness to choose the agent i.

$$\zeta_{ij} = w_1 b_{ij} - w_2 F_{ij}, \tag{28}$$

where b_{ij} is the bid of agent i for task j, w_1 and w_2 are the corresponding weight coefficients, and F_{ij} is the fitness of agent i for task j. Equation 28 indicates that the seller has considered not only the buyer's bid but also the fitness of agent i for task j. Under the same bidding conditions, the seller prioritizes the agent with higher fitness as the final counterparty; that is, the task holder gives preference to the agent most suitable for performing its own task.

4.3 Payment rules

After determining the matching relationship between the seller and the buyer, the final payment price depends on the payment rules formulated in this study. Payment rules are crucial for ensuring the incentive compatibility of the auction mechanism. In the Vickrey auction mechanism [30], the highest bidder wins, but the actual transaction price paid is the second highest bid. This auction mechanism motivates buyers to bid according to their true expected profits. Therefore, this study draws inspiration from the payment rules of the Vickrey auction mechanism, in which the seller uses the second highest bid b'_{ij}, immediately below the current winning buyer bid b_{ij}, as the transaction price p_{ij}.

The key to determining payment rules lies in how the second highest bid is obtained. The main idea of implementing the payment rules in this study is to sort the bids in the bid set and select the bid b'_{ij}, which is second only to the winning bid b_{ij}, as the transaction price p_{ij} that the winning bidder needs to pay. The actual final profit pro_{ij} of the buyer is presented in Equation 29:

$$pro_{ij} = \gamma_{ij} - p_{ij}. \tag{29}$$

4.4 Algorithm workflow

The flow of the algorithm proposed in this study is shown in Figure 1. First, the task fitness is calculated based on the relevant information of the task and the agent. Second, the agent calculates the expected revenue and selects the task with the largest revenue for bidding. Then, the seller receives the bid from the buyer and selects the buyer for task allocation. It is worth noting that the buyer is chosen by the seller based on a consideration of cost-effectiveness. Finally, the algorithm stops iterating when all the tasks have been allocated.

4.5 Task benefit and multi-agent benefit analysis

An effective auction mechanism should meet three attributes: incentive compatibility, individual rationality, and computational efficiency.

Incentive compatibility: incentive compatibility refers to motivating buyers to bid as high as possible within their own capabilities to achieve successful bidding, ensuring that the bid is genuine, without the possibility of falsely offering a high price but

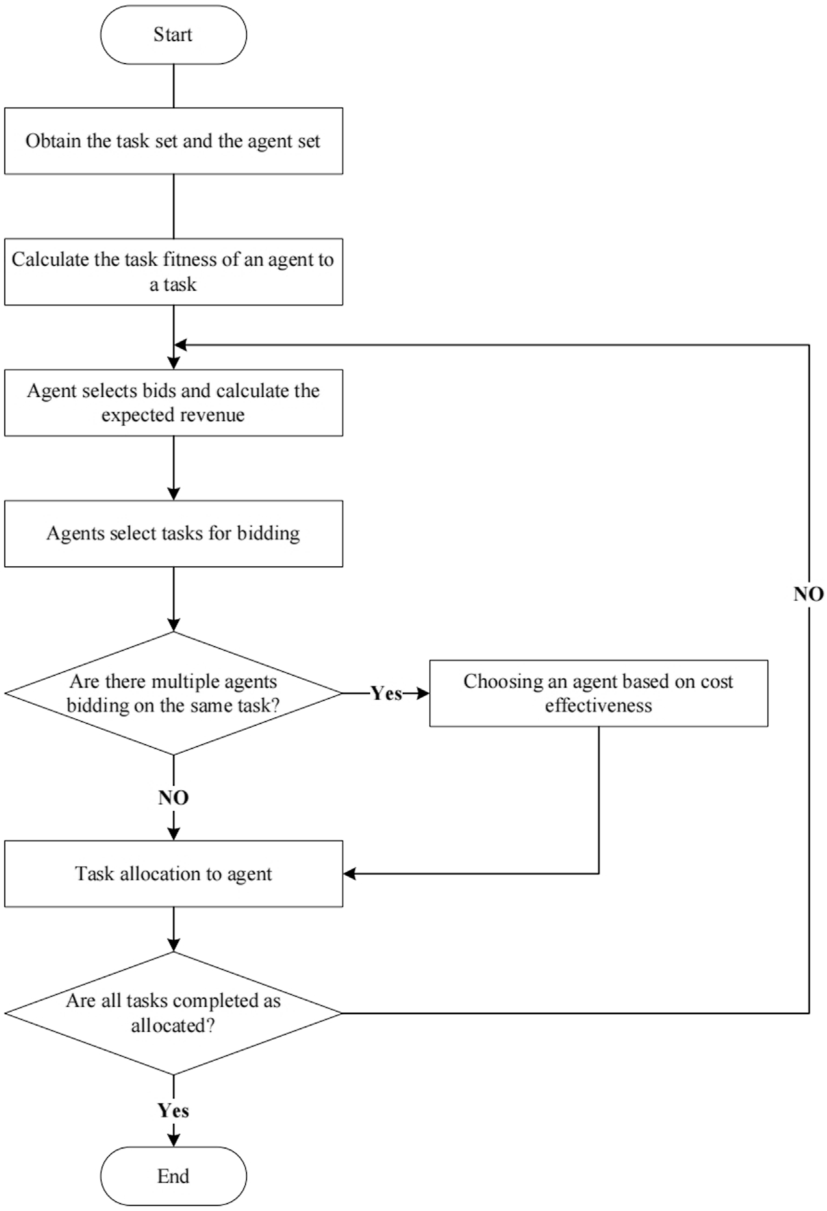

FIGURE 1
Algorithm workflow.

being unable to pay the final transaction price. This study adopts the second highest price b'_{ij} transaction principle, so the final transaction price p_{ij} is only lower than the bid of the successful bidder, that is, $b'_{ij} < b_{ij}$. The expected final profit $epro_{ij} = \gamma_{ij} - b_{ij}$ is calculated by the buyer during bidding, whereas the actual final profit $pro_{ij} = \gamma_{ij} - b'_{ij}$ is determined after adopting the second highest price transaction principle; as pro_{ij} is greater than $epro_{ij}$ calculated during bidding, this ensures that pro_{ij} of the buyer is higher than $epro_{ij}$ calculated during bidding, thereby encouraging the buyer to bid. Buyers are more willing to increase the bid price b_{ij} within the expected profit range γ_{ij} to their chances of successfully bidding the task. Therefore, this study effectively ensures the incentive compatibility of the FMMRA mechanism through the second highest price transaction principle.

Individual rationality: individual rationality refers to the fact that the buyer's bidding behavior and the seller's reverse selection rules are beneficial to oneself. The distribution coefficient $x_{ij} = 0$ of unsuccessful buyers indicates that the actual profit of the buyer is 0, and the buyer does not lose or make a profit. If $x_{ij} = 1$, meaning that the agent as the buyer chooses the task with the highest expected final profit $epro_{ij}$ for bidding, the task with higher $epro_{ij}$ will yield a greater actual final profit pro_{ij} for the agent after the second-price sealed bidding determines the final transaction price, thus satisfying individual rationality.

TABLE 2 Parameter setting.

Parameter	Range
A_i^{comp}, A_j^{move}, A_i^{dec}, A_j^{def} and A_j^{fight}	[0, 0.8]
A_i^{val}	[1, 10]
T_j^{comp}, T_j^{move}, T_j^{dec}, T_j^{def} and T_j^{fight}	[0, 0.8]
T_j^{val}	[20, 30]
L_{ij}	[1, 10]
Oil_{ij}	[1, 10]
$Cost_{ij}$	[1, 10]
b_{ij}	[10, 29]
Cnt_i	[2, 9]
f_β^{ij}	[5, 20]
w_1	0.3
w_2	0.7
ζ	0.1

5 Simulation and performance analysis

5.1 Setting

The number of tasks is set to 4, and the range of agents is $[8, 36]$. A judgment matrix is randomly generated, using the calculation formulae of the consistency ratio CI and the random consistency ratio CR to verify the rationality of the judgment matrix. If it is not reasonable, it is regenerated. After obtaining the judgment matrix, the importance weight coefficient $W = \left[\lambda_1^j, \lambda_2^j, \ldots, \lambda_\alpha^j\right]$ of the attributes of task j is determined based on the eigenvectors corresponding to the calculated maximum eigenvalue. The other parameters are shown in Table 2.

5.2 Performance analysis

The first-price auction algorithm, the second-price auction algorithm, the multi-round sealed sequential composite auction (MSSCA) algorithm proposed in [31], the FMMRA only considering fitness, and the average actual final profit of agents, the total satisfaction of agents, the task cost-effectiveness, and the total fitness of tasks of the FMMRA are compared and analyzed under different number of agents. Among them, the MSSCA algorithm does not consider the fitness of intelligent tasks and dynamically increases the price when the auction fails. In this study, the agent satisfaction is defined as the ratio of the agent's final bid to the final transaction price.

The number of tasks is a fixed value of 4, and the average final profit of agents with different numbers of agents is shown in Figure 2. From Figure 2, it can be observed that the second-price auction algorithm yields the highest average final profit for the agent, which is 6.64% higher than that of the FMMRA on average, followed by the first-price auction algorithm, which is 5.04% higher than that of the FMMRA on average. Due to the fixed income of the task and the cost of the agent executing the task, the difference between the task income and the task cost is equal to the sum of the agent's final profit and the final transaction price received by the task. Therefore, the FMMRA that incorporates a dynamic bidding strategy has increased the economic income indicators of the task holder by 5.04% and 6.64%, compared to the first-price auction algorithm and the second-price auction algorithm, respectively, which do not use a dynamic bidding strategy. The MSSCA algorithm, the FMMRA only considering fitness, and the FMMRA all use the dynamic bidding strategy designed in this study, so the final average profit of the agents of the second-price auction algorithm and the first-price auction algorithm is higher than that of the other three algorithms.

The purpose of the algorithm in this study is to maximize the cost-effectiveness of the task holder, allowing an intelligent user to increase their bid after a failed auction without knowing the bids of other agents, thereby improving their chances of success in the next auction. The price is the weighted sum of the bid and fitness. The cost-effectiveness of the agent will be improved by increasing the bid through the dynamic pricing strategy. The task holder selects the agent with high cost-effectiveness as the final transaction party; therefore, the agent's increasing bid will increase the probability of being selected by the task holder. The task holder increases the cost-effectiveness of the agent bidding for the task due to the dynamic markup of the agent, thereby achieving the goal of improving the cost-effectiveness of the task in this study. That is, the auction algorithm using a dynamic markup algorithm has a lower average final profit than the auction algorithm without dynamic markup.

Considering a fixed value of 4 for the number of tasks, the total cost-effectiveness curve for tasks with different numbers of agents is shown in Figure 3.

It can be observed from Figure 2 that the total cost performance of the FMMRA is 2.63% higher than that of the first-price auction algorithm, 5.47% higher than that of the second-price auction algorithm,1.45% higher than that of the MSSCA algorithm, and 1.83% higher than that of the FMMRA only considering fitness. This is because the FMMRA proposed in this study uses cost-effectiveness as the indicator for the task holder to select the agent in the buyer matching phase. The cost-effectiveness is defined as the weighted sum of the agent's bid and the agent's fitness to the task. Therefore, the FMMRA achieves the goal of maximizing the total cost-effectiveness of the tasks; that is, the results of multi-agent task allocation achieve the best combination of economic benefits (agent bid) and completion effects (task fitness).

Considering that the number of tasks is a fixed value of 4, the total fitness curve of tasks with different number of agents is shown in Figure 4.

It can be observed from Figure 4 that the FMMRA only considering fitness improves the performance of the overall fitness index of the task by 0.66% compared with the FMMRA, 1.39% compared with the MSSCA algorithm, 1.52% compared with the second-price auction algorithm, and 1.52% compared with the first-price auction algorithm. Task fitness is the only criterion for task holders to select agents in the FMMRA that only considers fitness, and the result of task allocation must be reflected in the

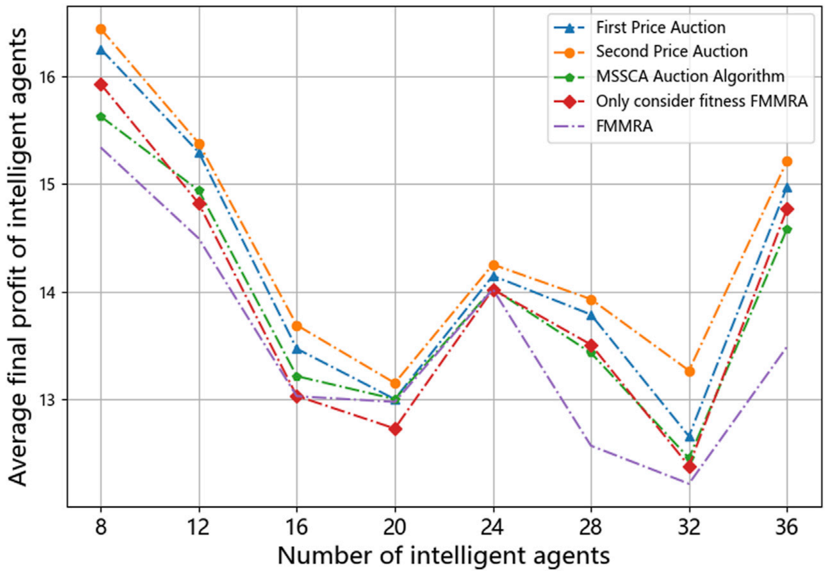

FIGURE 2
Comparison chart of the average final profit of agents.

FIGURE 3
Total cost-effectiveness curve.

overall fitness index of the task. The FMMRA in this study takes the weighted sum of task fitness and agent bid; that is, the cost-effectiveness of the agent, as the reverse selection criteria, and partially considers the task fitness index. The MSSCA algorithm, the second-price auction algorithm, and the first-price auction algorithm do not consider the fitness factor of the task in the buyer matching phase and only make reverse selection based on the agent bid. Therefore, the FMMRA in this study is only lower than the FMMRA only considering adaptation in terms of the fitness index and higher than the first-price auction algorithm, the second-price auction algorithm, and the MSSCA algorithm. The allocation results of the first-price auction algorithm and the second-price auction algorithm are the same and differ only in the final transaction price, so the broken lines are coincident in the overall fitness index of the task.

In conclusion, under the condition of a fixed number of tasks and different numbers of agents, FMMRA, a distributed auction approach based on maximizing cost-effectiveness, proposed in this study, achieves a task cost-effectiveness index that is 1.83% higher than that of the FMMRA without considering the fitness of intelligent tasks, 1.45% higher than that of the MSSCA algorithm, 5.47% higher than that of the second-price auction algorithm, and

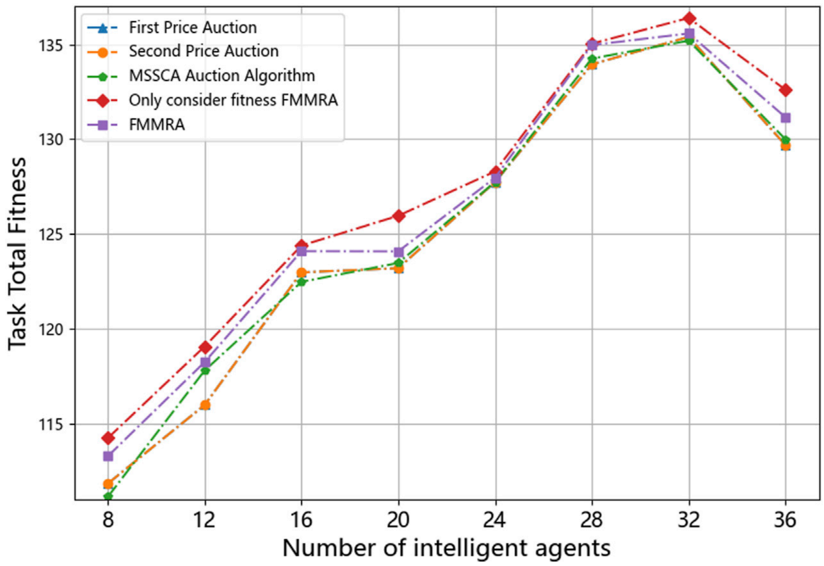

FIGURE 4
Comparison chart of total fitness of tasks.

2.63% higher than that of the first-price auction algorithm. The result of multi-agent task allocation achieves the best comprehensive economic benefit (agent bid) and completion effect (task average fitness), and can adapt to the changing number of agents.

6 Conclusion

In this study, we addressed the multi-agent task allocation problem from a new perspective by simultaneously considering the economic benefit of agents and the mission-oriented effectiveness of tasks. To this end, we proposed an FMMRA that explicitly integrates task fitness evaluation and cost–benefit analysis into the distributed auction framework. First, we constructed a comprehensive task fitness model using an AHP-based multi-attribute decision mechanism to quantitatively measure the matching degree between agents' capabilities and task requirements. Then, we introduced a cost-effectiveness metric that jointly accounts for the bidding value and task fitness, ensuring that the selected agent is not only willing to undertake the task but also the most suitable to accomplish it. Based on this metric, a multi-round auction mechanism with adaptive bidding and a Vickrey-based payment rule was designed to guarantee incentive compatibility, individual rationality, and computational feasibility. Extensive simulations demonstrated the effectiveness of the proposed approach. Compared with classical first-price, second-price, and MSSCA mechanisms, the FMMRA consistently achieves higher task cost-effectiveness while maintaining high task fitness and agent utility. In particular, the proposed method improves the overall cost-effectiveness by up to 5.47%, increases agent satisfaction and provides a more balanced allocation between economic return and mission performance. These results clearly verify that the proposed mechanism can significantly enhance decision quality in multi-agent task allocation scenarios.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

YZ: Software, Data curation, Conceptualization, Writing – review and editing, Formal analysis, Writing – original draft. QL: Writing – review and editing, Conceptualization, Formal analysis, Data curation, Writing – original draft. XY: Writing – review and editing, Conceptualization, Writing – original draft, Software, Data curation, Methodology. LW: Data curation, Methodology, Writing – review and editing, Formal analysis, Writing – original draft. GL: Writing – review and editing, Writing – original draft, Data curation, Supervision, Methodology. SL: Methodology, Supervision, Data curation, Writing – review and editing. TL: Validation, Supervision, Writing – review and editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript

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