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Research Article

Research on Fuzzy Decision-Making Method of Task Allocation for Ship Multiagent Collaborative Design

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Since task allocation is one of the core tasks of ship design, the choice of its allocation strategy is a key factor that affects whether the task and the design agent can be beneficially matched. Different from the traditional one-way assignment mode of assigning tasks to designers, in the task assignment strategy of modern ship collaborative design mode, designers' ability and benefit ratio is getting higher and higher. Therefore, in order to improve the efficiency and quality of task design, this paper proposes a multidesign agent-task allocation decision-making method. In this paper, the task attributes and designers' attributes are introduced into the task allocation strategy model, and the fuzzy linguistic variable method is used to build the evaluation index matrix of the design agent, and the task timeliness function is established. Secondly, the multidesign agent-task benefit function is established and solved to obtain the best allocation strategy. Finally, through example verification and comparative analysis with the Round-Robin algorithm (RR) and the Weighted Round-Robin (WRR) algorithm, the validity, feasibility, and stability of the multidesign agent-task allocation decision-making method proposed in this paper are verified, and it is proved that the task allocation method takes the bilateral needs of the task and the design agent into account, solves the optimal allocation strategy of collaborative design tasks, and realizes the balanced allocation between the ship collaborative design task and the design agent.

1. Introduction

Ship product design is an extremely complex process that requires the participation of multiple departments and professionals. In order to shorten the ship design cycle, meet the coordination and communication between designers, and improve the quality of ship design, domestic ships are gradually turning to a collaborative design model. The collaborative design of modern ships is jointly completed by design institutes, shipyards, shipowners, classification societies, suppliers, subcontractors, and other entities. Due to the large volume of ships and a large number of design tasks, the agents participating in the design have different fields, knowledge background, and cooperation efficiency. How to choose a plan with appropriate design task granularity and optimal benefit between multiple design agents and tasks from many task allocation schemes is one of the key problems in the current research of ship collaborative design.

Task assignment is an important stage and link of collaborative design, and it is the communication between task assignor and task receiver. Reasonable task allocation can make full use of resources and assign tasks to the most appropriate executors, so that task executors can complete collaborative design tasks efficiently, low cost, and high quality, and finally improve the efficiency of collaborative design product design. At present, scholars at home and abroad have done a lot of research on the rational allocation of tasks and personnel. Some scholars take task assigners or task recipients as the research objects and take factors such as the skill level of personnel or the preference of task assigners as the research background to study how to improve the efficiency of task assignment and the degree of task completion. Gui et al. [1]

considered two task allocation situations of initial personnel alliance and joining new personnel to form a new alliance and established a task allocation strategy of task priority satisfaction and performance reward to meet the characteristics of task timeliness, stability, and dynamics. Jiang et al. [2] considered the user's learning ability, modeled the user's skill update method in the process of performing tasks, proposed a user skill update mechanism, established a task allocation function that maximizes the number of tasks completed, and applied an improved whale algorithm. Solve task allocation problems. Wang et al. [3] introduced a minimum perceived quality threshold for tasks in the context of a multitasking assignment problem, which improves the perceived quality of individual tasks by considering the maximum number of tasks allowed for the personnel, thus improving the overall utility of the task. Wu et al. [4] proposed an algorithm capable of real-time task assignment and budget awareness based on personnel maximization of desired outcomes with a finite task budget in the context of spatial task package assignment, which was verified to be effective in improving task assignment efficiency. Jiang et al. [5] proposed a group-oriented approach to measure the ability of a group to complete a task in terms of contextual crowdsourcing value and constructed a task allocation algorithm to rationally allocate tasks and people. Li and Zhang [6] considered two types of time-constrained properties, task timeliness, and personnel availability and designed two types of evolutionary algorithms to solve the multitask assignment problem with time constraints. Most of the above scholars take the maximum ability or quantity limit of task recipients as the realistic constraints and take improving the efficiency of task allocation as the ultimate goal. Some scholars also take the skill level of task recipients as the influencing factor of task quality. While choosing different research subjects, scholars design corresponding functional relations to measure the timeliness and quality of task completion in combination with the specific environmental background of task allocation.

In task allocation, resources are an important element that affects the balance of task allocation. Many scholars have carried out research on the impact of resources on task allocation. Huang at al. [7] used idle vehicle resources as the background to construct the coordinated task processing calculation paradigm CVEC for parked vehicles and MEC servers and studied how to perform effective workload distribution and maximize user center utility in a dynamic environment to optimize network task scheduling. Xu et al. [8] aimed at the low utilization rate of collaborative logistics task resource allocation and the conflict of interest between operators and customers. Based on the multidistribution hybrid collaborative network, considering factors such as task delay penalties and capacity limitations, they formulated a multiobjective and multilogistics task scheduling strategy and designed an immune genetic algorithm with a three-layer coding mechanism to solve the model. Rajakumari et al. [9] introduced cloud computing resources, system throughput, and execution time in the context of cloud computing task scheduling problem, maximized resource utilization, minimized system throughput, and minimized execution waiting time as objective functions, thus designing a cloud computing fuzzy hybrid particle swarm parallel ant colony optimization algorithm. Baroudi et al. [10] studied the online dynamic multirobot task assignment problem and constructed a distributed multiobjective task assignment method with the task quality level as the optimization objective, while considering task distance and load balancing. Lee [11] proposed a resource-based multirobot task allocation algorithm with task completion timeliness and resource consumption effectiveness as the research objectives, so as to improve task efficiency and effectiveness. Yang et al. [12] designed a node affinity-based task assignment method for the wireless sensor task assignment problem under resource constraints and also to reduce node task redundancy. Most of the task assignment problems related to resource influencing factors focus on multiuser system application fields such as logistics, cloud computing, and multirobot system. In view of the task allocation problem in the above multiuser system application fields, scholars also limited the types of key resources. In the above study, resources were limited to network computing resources, robot use resources, logistics vehicles, and other consumable resources, and allocation constraints were applied to the application of system resources.

At the same time, some scholars focus their research on task allocation decision-making methods and use different algorithms to innovate problem solving methods. Song et al. [13] took the multirobot system in the medical and nursing environment as the application background and proposed a group intelligent allocation scheme based on the near-field task subset division. Firstly, the tasks are arranged orderly by ant colony algorithm to determine an optimal task chain, and then, the task chain is divided into subsets by genetic algorithm. Hu et al. [14] proposed a multiobjective reinforced greedy iterative algorithm to solve the task allocation and scheduling among mobile smart users. At the macro level of the algorithm, the Q-learning reinforcement learning algorithm is used to optimize learning, and at the micro level, the greedy algorithm is used to select the iterative optimal solution, and it is verified that the proposed algorithm has fast convergence speed and low energy consumption. Feng et al. [15] proposed a group intelligence-aware user task allocation mechanism, which combines vehicle user trajectory characteristics with combinatorial multiarmed bandit (CMAB) algorithm to improve the accuracy of task allocation. Ye et al. [16] used the cooperative multitask assignment of the UAV to perform the suppression of enemy air defense (SEAD) mission on the ground stationary target as the research goal. In order to solve the problems faced in task allocation, such as large scale, heterogeneity of UAV, different task coupling, and task priority constraints, an improved genetic algorithm with multitype gene chromosome coding strategy is proposed, and the optimization performance of the algorithm is verified by simulation. Shi et al. [17] proposed a dynamic auction approach for differentiated tasks under cost rigidities (DAACR) in the context of a multirobot system, which was validated to reduce the task assignment delay time of a multirobot system, while the algorithm can be applied to multirobot systems with different work contexts, thus improving the overall utilization of the robot system. Zhang et al. [18] extended their research on the existing status of UAV swarm task preprocessing to construct a discrete particle swarm algorithm that introduces a market auction mechanism to study the dynamic task assignment problem during task execution, with the objective of real-time task assignment for UAV swarms. Yin et al. [19] constructed a group intelligent software development task assignment method based on the heterogeneity of software development tasks in the context of software development task assignment in P2P networks by transforming the task assignment problem into an optimization problem and modeling the task assignment process through Hidden Markov models. Zhang et al. [20] combined cloud computing and smart grid and constructed a new smart grid cloud task scheduling strategy to solve the cloud task scheduling problem with minimizing task completion time and minimizing task execution cost as the objectives. Gong et al. [21] constructed the eco-friendly task assignment algorithm (EFTA) to solve the task assignment problem of minimizing carbon emissions under constraints such as task duration and road traffic constraints. Wu et al. [22] constructed an unmanned submersible-mission matching matrix while introducing temporal path and voyage impact constraints to design a dynamic extended consistency set algorithm based on the consistency algorithm. Nedjah et al. [23] proposed a clustered dynamic task assignment algorithm in order to improve the efficiency of robot population task assignment coordination, which guides the robot to complete the exploration of the assigned space at an adaptive rate. Zhao et al. [24] proposed a fast task assignment algorithm based on Q-learning algorithm to solve the task assignment problem of heterogeneous UAVs in uncertain environments. There are a variety of algorithm innovations in task allocation, most of which are based on heuristic algorithms such as particle swarm algorithm and genetic algorithm. According to the actual environment background of task allocation, new algorithms are introduced to update and improve strategies. Some scholars apply reinforcement learning algorithms to obtain better task allocation strategies through the expansibility of reinforcement learning.

The above literature studies task allocation strategies from different perspectives but only discusses one type of task recipients and does not consider the existence of multiagent task recipients, that is, the task recipients come from different units and have different fields and disciplines. And the collaboration efficiency between task recipients is also different. In addition, the literature has more research on the number and quality of task completion, task completion efficiency, and other issues, and less consideration is given to the relationship between task completion timeliness, task completion benefits and personnel attributes, and task attributes. That is to say, there is less research on the attributes of both tasks and personnel at the same time. At present, most of the research in the field of ship collaborative design focuses on how to apply computer technology and digital technology to improve the parallelism and professionalism of ship design process and finally improve the design quality and efficiency, for example, the secondary development of modeling software to enable the integration of complex and large span of expertise or to explore the application and verification of the ship design field of the full three-dimensional model and simulation of the full coverage system. These studies mainly focus on the design itself, while task management is also very important to improve the design efficiency as the first step of design. At present, the task management level of ship field is in the development stage, and the assignment of design task mainly adopts the way of combining manual and computer. The task manager selects the task and the task receiver and centrally distributes the task through the computer system. When task managers assign tasks, most of them consider the professional suitability of designers and the time occupation of designers, and less consider the collaboration between designers in task collaboration. At the same time, the literature has less research on the problems in the field of ship design task allocation. As a complex product, ship design tasks are complex, design tasks are time-sensitive, oriented to many professions, and require high skills for designers. At the same time, designers usually come from different units. Reasonably allocate tasks so that tasks can be assigned to the most suitable personnel at the first time, so that designers with different specialties and abilities can coordinate their work in a unified way and improve the task execution rate. To sum up, it is very important to take intelligent research on ship design task allocation strategy.

The designer's ability attribute is an important factor that affects the result of task assignment decision. Competent and efficient designers tend to have low rework rates and high-quality tasks. In general, the description of designer capability attributes is inaccurate and vague. For example, terms such as general, good, and very good can be used to evaluate the designer's negotiation and communication ability, but it cannot be expressed by precise value. How to quantitatively measure the attribute value of ability is also a problem that needs to be explored and solved in this paper. A practical method is to replace numerical evaluation with fuzzy linguistic variable evaluation and to solve complex, unstructured, and nonquantitative problems by taking the words and sentences as the value of fuzzy linguistic variable. Some scholars use fuzzy sets, fuzzy soft sets, and other theories to solve group decision-making and multiobjective decision-making problems. Garg et al. [25] combined with the advantages of interval valued spherical fuzzy sets and complex numbers and proposed complex interval valued t-sphere fuzzy sets (CIVTSFS); Siddique et al. [26] introduced algebraic operation into Pythagorean fuzzy soft set (PFSS) and proposed a PFSS decision method based on score matrix; Akram et al. [27] extended and generalized the q-order graph fuzzy set (q-RPFS) to solve the multiobjective decision-making problem. Some scholars have also extended the fuzzy super soft set. Ihsan et al. [28] introduced a new extended fuzzy parameterization model in the Pythagorean fuzzy super soft expert set; Rahman et al. [29] proposed two new structures: fuzzy parameterized intuitionistic fuzzy hypersoft set (fpifhs-set) and fuzzy parameterized neutrosophic hypersoft set (fpnhs-set); Debnath [30] describes the related operations of fuzzy super soft sets.

To sum up, through the above literature analysis and discussion, based on the background of ship collaborative design, this paper selects a certain stage of ship production design, considering that the recipient of the design task is multiple design agents from different units such as shipyard design department, suppliers, design subcontractors, and classification societies. The professional attributes and collaboration rate between design agents are introduced into the problem-solving model, and a task assignment decision algorithm for ship multiagent collaborative design based on the design agent's professional attributes, ability attributes, design efficiency, design rework rate, and collaboration rate between design agents is proposed. This paper constructs the task timeliness function, sets the design agent evaluation index matrix by introducing the fuzzy linguistic variable method, then constructs the multidesign agent-task benefit function, and obtains the task allocation strategy by solving the benefit function value, so as to realize the distribution balance between multidesign agents and tasks, improve the design efficiency, and shorten the design cycle.

The chapters of this paper are arranged as follows. In Section 2, we set up a five-tuple allocation decision model including design task elements, design agent elements, design task attribute elements, design agent attribute elements, and benefit function elements. In Section 3, we set the value range or value set of each attribute in the design agent attribute matrix, construct the evaluation matrix through the fuzzy linguistic variable method, establish the task timeliness function, and finally establish the benefit function. In Section 4, we take a certain stage of ship collaborative design as an example to verify and take polling algorithm and weighted polling algorithm as comparison methods to verify the effectiveness and stability of the multiagent task allocation decision-making method for ship collaborative design proposed in this paper. Finally, Section 5 summarizes this paper and discusses the future work.

2. Multidesign Agent-Task Allocation Decision Model

Based on the task allocation in the subdesign stage of ship production design, the collaborative units in this design stage include shipyards, suppliers, design subcontractors, and classification societies. The production design tasks at this stage involve structure, piping, outfitting, hull, interior installation, and other majors. In the ship design business, a hull section design project is used as a design task package, which includes tasks for various design agents in various disciplines and types.

The distribution decision model should have the characteristics of being able to completely describe the problem background and abstract the content of the problem. Based on the above design objectives, it is defined as follows.

Definition 1. Set the distribution decision model elements and specifies the distribution decision model as a five-tuple:

$$\text{Model} = \langle T, D, Q_T, Q_D, V \rangle. \tag{1}$$

The specific meanings of allocation decision model elements and their decomposition elements are shown in Table 1.

2.1. Design Task Model Elements. T represents the design task matrix. m represents the number of all hull section design tasks in the task set, and T_i represents a hull section design project, including various professional design tasks for multiple design agents. n represents the number of design tasks in a design project. In summary, the design tasks are defined as follows.

$$\begin{aligned} T &= [T_1, T_2 \cdots T_m]^T, \\ T_i &= [T_{i1}, T_{i2} \cdots T_{\text{in}}]. \end{aligned} \tag{2}$$

A design task matrix T contains all design tasks.

$$T = \begin{bmatrix} T_{11} & T_{12} & \cdots & T_{1n} \\ T_{21} & T_{22} & \cdots & T_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ T_{m1} & T_{m2} & \cdots & T_{mn} \end{bmatrix}. \tag{3}$$

Among them, T_{ij} is the subtask j in the task item i,

$$\begin{cases} i = 1, 2, \cdots, m, \\ j = 1, 2, \cdots, n. \end{cases} \tag{4}$$

That is, after the task is decomposed, it is the most fine-grained subtask suitable for task allocation.

2.2. Model Elements of the Design Agent. D represents the design agent matrix. Designers are divided based on unit departments, such as shipyard structural design department, shipyard piping design department or suppliers, and design subcontractors, with a unit department as a design agent.

k represents the number of design agents involved in the task, and D_i represents a design agent, including multiple designers who can receive design tasks. l represents the number of designers who can accept tasks in a design agent. In summary, the design agent is defined as follows.

$$\begin{aligned} D &= [D_1 D_2 \cdots D_k]^T, \\ D_1 &= [D_{i1} D_{i2} \cdots D_{il}]. \end{aligned} \tag{5}$$

A design agent matrix D that contains all designers.

$$D = \begin{bmatrix} D_{11} & D_{12} & \cdots & D_{1l} \\ D_{21} & D_{22} & \cdots & D_{2l} \\ \vdots & \vdots & \cdots & \vdots \\ D_{k1} & D_{k2} & \cdots & D_{kl} \end{bmatrix}, \tag{6}$$

where D_{pq} is the designer q in the design agent p.

2.3. Model Elements for Design Task Attributes.

$$Q_T = \{Q_{TA}, ,Q_{TC}, Q_{TE}\}. \tag{7}$$

Q_T represents a collection of design task attributes.

Table 1: Model elements definition.

Elements	Meaning
$\boldsymbol{T}$	The design task matrix
$\boldsymbol{D}$	The design agent matrix
Q_T	Collection of design task attributes
Q_D	Collection of design agent attributes
$\boldsymbol{V}$	The benefit function matrix
$\boldsymbol{m}$	The number of all hull section design tasks in the task set
$\boldsymbol{n}$	The number of design tasks in a design project
T_{ij}	The subtask j in the task item i, $1 \leq i \leq m$; $1 \leq j \leq n$
$\boldsymbol{k}$	The number of design agents involved in the task
$\boldsymbol{l}$	The number of designers who can accept tasks in a design agent
D_{pq}	The designer q in the design agent p, $1 \leq p \leq k$; $1 \leq q \leq l$
Q_{TA}	The matrix of the number of designers
$Q_{TA_i^j}$	The number of designers required to complete the task T_{ij}
Q_{TC}	The rated completion time matrix required to complete the task
$Q_{TC_i^j}$	The rated time required to complete the task T_{ij}
Q_{TE}	Represents the average amount of tasks
$Q_{TE_i^j}$	The average amount of tasks occupied by a single designer in completing the T_{ij} task
Q_{Df}	The professional attribute matrix of the design agent
$\widehat{Q}_{Df_i^j}$	The professional attribute value matrix of all design agents D for the design task T_{ij}
${}_p^q\widehat{Q}_{Df_i^j}$	The professional attribute value of a single designer D_{pq} for the design task T_{ij}
Q_{Dgx}	The attribute matrix of negotiation and communication ability of the design agent
$Q_{Dgx_p^q}$	The attribute value of the negotiation and communication ability of the designer D_{pq}
Q_{Dgy}	The analysis and planning ability attribute matrix of the design agent
$Q_{Dgy_p^q}$	The attribute value of the analysis and planning ability of the designer D_{pq}
Q_{Dgz}	The attribute matrix of the design agent's practical execution ability
$Q_{Dgz_p^q}$	The attribute value of the practical execution ability of the designer D_{pq}
Q_{Dh}	The design efficiency matrix of the design agent
$Q_{Dh_p^q}$	The task design efficiency of the designer D_{pq}
Q_{Dl}	The design rework rate matrix of the main body of the design
$Q_{Dl_p^q}$	The design rework rate of the designer D_{pq}
Q_{Do}	The coordination rate matrix of the design agent
$Q_{Do_p^q}$	The value of the synergy rate of the designer D_{pq}
U_{ij}^{pq}	The timeliness function of the designer D_{pq} to the design task T_{ij}
$\boldsymbol{\Phi}$	The task quantity evaluation matrix that defines the design task
V_{ij}^{pq}	The T_{ij} benefit function of selecting the designer D_{pq}

(1)Q_{TA} represents the matrix of the number of designers required by the task specification

$$Q_{TA}=\begin{bmatrix} Q_{TA_1^1} & Q_{TA_1^2} & \cdots & Q_{TA_1^n} \\ Q_{TA_2^1} & Q_{TA_2^2} & \cdots & Q_{TA_2^n} \\ \vdots & \vdots & \cdots & \vdots \\ Q_{TA_m^1} & Q_{TA_m^2} & \cdots & Q_{TA_m^n} \end{bmatrix}. \quad (8)$$

$Q_{TA_i^j}$ represents the number of designers required to complete the task T_{ij}.

(2)Q_{TC} represents the rated completion time matrix required to complete the task

$$Q_{TC}=\begin{bmatrix} Q_{TC_1^1} & Q_{TC_1^2} & \cdots & Q_{TC_1^n} \\ Q_{TC_2^1} & Q_{TC_2^2} & \cdots & Q_{TC_2^n} \\ \vdots & \vdots & \cdots & \vdots \\ Q_{TC_m^1} & Q_{TC_m^2} & \cdots & Q_{TC_m^n} \end{bmatrix}. \quad (9)$$

$Q_{TC_i^j}$ represents the rated time required to complete the task T_{ij}. This task needs to be completed within the specified time; otherwise, the task is overdue and requires corresponding overdue penalties.

(3)Q_{TE} represents the average amount of tasks

$$Q_{TE}=\begin{bmatrix} Q_{TE_1^1} & Q_{TE_1^2} & \cdots & Q_{TE_1^n} \\ Q_{TE_2^1} & Q_{TE_2^2} & \cdots & Q_{TE_2^n} \\ \vdots & \vdots & \cdots & \vdots \\ Q_{TE_m^1} & Q_{TE_m^2} & \cdots & Q_{TE_m^n} \end{bmatrix}, \quad (10)$$

$$Q_{TE_i^j}=\frac{1\times Q_{TC_i^j}}{Q_{TA_i^j}}. \quad (11)$$

$Q_{TE_i^j}$ represents the average amount of tasks occupied by a single designer in completing the T_{ij} task. The larger the value, the greater the average workload of the task.

$$\begin{cases} \mathrm{MAX}Q_{TE}=\max\sum_{j=1}^{n}\sum_{i=1}^{m}Q_{TE_i^j}, \\ \mathrm{MIN}Q_{TE}=\min\sum_{j=1}^{n}\sum_{i=1}^{m}Q_{TE_i^j}, \\ q_{te_i^j}=\dfrac{Q_{TE_i^j}-\mathrm{MIN}Q_{TE}}{\mathrm{MAX}Q_{TE}-\mathrm{MIN}Q_{TE}}, q_{te_i^j}=[0,1], \\ i=1,2,\cdots,m, j=1,2,\cdots,n. \end{cases} \quad (12)$$

The average task load is normalized and dimensionless, and its value range is [0,1].

2.4. Model Elements for Design Agent Attributes.

$$Q_D=\left\{Q_{Df},Q_{Dg},Q_{Dh},Q_{Dl},Q_{Do}\right\}. \quad (13)$$

Q_D represents a collection of design agent attributes.

(1) Q_{Df} is the professional attribute matrix of the design agent. It indicates the degree of professional Matching between the design agent and the design task.

$$\begin{gathered} Q_{Df}=\left[\widehat{Q}_{Df_i^j}\right]_{m\times n}; \widehat{Q}_{Df_i^j}=\left[{}_p^q\widehat{Q}_{Df_i^j}\right]_{k\times l}, \\ Q_{Df}=\begin{bmatrix} \widehat{Q}_{Df_1^1} & \widehat{Q}_{Df_1^2} & \cdots & \widehat{Q}_{Df_1^n} \\ \widehat{Q}_{Df_2^1} & \widehat{Q}_{Df_2^2} & \cdots & \widehat{Q}_{Df_2^n} \\ \vdots & \vdots & \cdots & \vdots \\ \widehat{Q}_{Df_m^1} & \widehat{Q}_{Df_m^2} & \cdots & \widehat{Q}_{Df_m^n} \end{bmatrix}, \\ \widehat{Q}_{Df_i^j}=\begin{bmatrix} {}_1^1\widehat{Q}_{Df_i^j} & {}_1^2\widehat{Q}_{Df_i^j} & \cdots & {}_1^l\widehat{Q}_{Df_i^j} \\ {}_2^1\widehat{Q}_{Df_i^j} & {}_2^2\widehat{Q}_{Df_i^j} & \cdots & {}_2^l\widehat{Q}_{Df_i^j} \\ \vdots & \vdots & \cdots & \vdots \\ {}_k^1\widehat{Q}_{Df_i^j} & {}_k^2\widehat{Q}_{Df_i^j} & \cdots & {}_k^l\widehat{Q}_{Df_i^j} \end{bmatrix}. \end{gathered} \quad (14)$$

Among them, $\widehat{Q}_{Df_i^j}$ represents the professional attribute value matrix of all design agents D for the design task T_{ij}. ${}_p^q\widehat{Q}_{Df_i^j}$ represents the professional attribute value of a single designer D_{pq} for the design task T_{ij}.

(2)Q_{Dg} represents the set of design main body's ability attributes

$$Q_{Dg}=\left\{Q_{Dgx},Q_{Dgy},Q_{Dgz}\right\} \quad (15)$$

(a)Q_{Dgx} is the attribute matrix of negotiation and communication ability of the design agent

$$Q_{Dgx}=\begin{bmatrix} Q_{Dgx_1^1} & Q_{Dgx_1^2} & \cdots & Q_{Dgx_1^l} \\ Q_{Dgx_2^1} & Q_{Dgx_2^2} & \cdots & Q_{Dgx_2^l} \\ \vdots & \vdots & \cdots & \vdots \\ Q_{Dgx_k^1} & Q_{Dgx_k^2} & \cdots & Q_{Dgx_k^l} \end{bmatrix}. \quad (16)$$

Among them, $Q_{Dgx_p^q}$ represents the attribute value of the negotiation and communication ability of the designer D_q^p.

(b)Q_{Dgy} is the analysis and planning ability attribute matrix of the design agent

$$Q_{Dgy}=\begin{bmatrix} Q_{Dgy_1^1} & Q_{Dgy_1^2} & \cdots & Q_{Dgy_1^l} \\ Q_{Dgy_2^1} & Q_{Dgy_2^2} & \cdots & Q_{Dgy_2^l} \\ \vdots & \vdots & \cdots & \vdots \\ Q_{Dgy_k^1} & Q_{Dgy_k^2} & \cdots & Q_{Dgy_k^l} \end{bmatrix}. \quad (17)$$

Among them, $Q_{Dgy_p^q}$ represents the attribute value of the analysis and planning ability of the designer D_{pq}.

(c)Q_{Dgz} is the attribute matrix of the design agent's practical execution ability

$$Q_{Dgz} = \begin{bmatrix} Q_{Dgz_1^1} & Q_{Dgz_1^2} & \cdots & Q_{Dgz_1^l} \\ Q_{Dgz_2^1} & Q_{Dgz_2^2} & \cdots & Q_{Dgz_2^l} \\ \vdots & \vdots & \cdots & \vdots \\ Q_{Dgz_k^1} & Q_{Dgz_k^2} & \cdots & Q_{Dgz_k^l} \end{bmatrix}. \quad (18)$$

Among them, $Q_{Dgz_p^q}$ represents the attribute value of the practical execution ability of the designer D_{pq}.

(3)Q_{Dh} is the design efficiency matrix of the design agent

$$Q_{Dh} = \begin{bmatrix} Q_{Dh_1^1} & Q_{Dh_1^2} & \cdots & Q_{Dh_1^l} \\ Q_{Dh_2^1} & Q_{Dh_2^2} & \cdots & Q_{Dh_2^l} \\ \vdots & \vdots & \cdots & \vdots \\ Q_{Dh_k^1} & Q_{Dh_k^2} & \cdots & Q_{Dh_k^l} \end{bmatrix}. \quad (19)$$

Among them, $Q_{Dh_p^q}$ is the task design efficiency of the designer D_{pq}.

(4)Q_{Dl} is the design rework rate matrix of the main body of the design

$$Q_{Dl} = \begin{bmatrix} Q_{Dl_1^1} & Q_{Dl_1^2} & \cdots & Q_{Dl_1^l} \\ Q_{Dl_2^1} & Q_{Dl_2^2} & \cdots & Q_{Dl_2^l} \\ \vdots & \vdots & \cdots & \vdots \\ Q_{Dl_k^1} & Q_{Dl_k^2} & \cdots & Q_{Dl_k^l} \end{bmatrix}. \quad (20)$$

Among them, $Q_{Dl_p^q}$ is the design rework rate of the designer D_{pq}.

(5)Q_{Do} is the coordination rate matrix of the design agent

$$Q_{Do} = \begin{bmatrix} Q_{Do_1^1} & Q_{Do_1^2} & \cdots & Q_{Do_1^l} \\ Q_{Do_2^1} & Q_{Do_2^2} & \cdots & Q_{Do_2^l} \\ \vdots & \vdots & \cdots & \vdots \\ Q_{Do_k^1} & Q_{Do_k^2} & \cdots & Q_{Do_k^l} \end{bmatrix}. \quad (21)$$

Among them, $Q_{Do_p^q}$ represents the value of the synergy rate of the designer D_{pq}.

2.5. Model Elements of Benefit Function. V represents the benefit function matrix.

$$V = \begin{bmatrix} V_{11} & V_{12} & \cdots & V_{1n} \\ V_{21} & V_{22} & \cdots & V_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ V_{m1} & V_{m2} & \cdots & V_{mn} \end{bmatrix}, V = \left[V_{ij}^{pq}\right]_{k\times l}. \quad (22)$$

Among them, V_{ij} is the benefit function of the subtask T_{ij}. The benefit function is constructed by selecting different designers and qualitatively processing their design attributes. The value of V_{ij} is calculated by selecting the task allocation strategy. The larger the value is, the more suitable the designer selected in the task allocation scheme is to the design task, and the stronger the balance between the design agent and the task.

The decomposition logic diagram of the multidesign agent-task allocation decision-making method proposed in this paper is shown in Figure 1.

3. Multidesign Agent-Task Allocation Decision-Making Strategy

The decision-making process of ship collaborative design task allocation is a complex coordinated decision-making process, and the bilateral needs between tasks and designers need to be considered at the same time. This paper is aimed at matching and balancing between design tasks and designers, taking the requirements of task allocation and the design needs of designers into account, and establishing a multiagent-task allocation decision-making model.

Through the above description of the multiagent-task allocation decision-making model, the model elements of design task, design agent, design task attribute, design agent attribute, and benefit function are set. The following will analyze in detail the process of establishing the benefit function based on the given model and its value.

Firstly, this paper sets the value range or value set of each attribute in the main design attribute matrix, then constructs the evaluation matrix through the fuzzy linguistic variable method, establishes the task timeliness function, and finally establishes the benefit function.

3.1. Evaluation Matrix Based on Fuzzy Linguistic Variables. In the process of assigning tasks and personnel, the character attributes of personnel and the task attributes of tasks are important influencing factors that affect the task assignment strategy and determine the effect of task completion. At present, scholars have conducted some researches on personnel and task attributes in task allocation. Jiang et al. [31] considered the staff's experience value and current load value of the task, matched the staff's role and skills with the task, and designed a task assignment algorithm based on the task and the staff's attributes. Wu et al. [32] introduced the concept of task personnel's personality ability attributes and comprehensive technical ability attributes in the task personnel matching process to provide decision support for task assignment. Tu

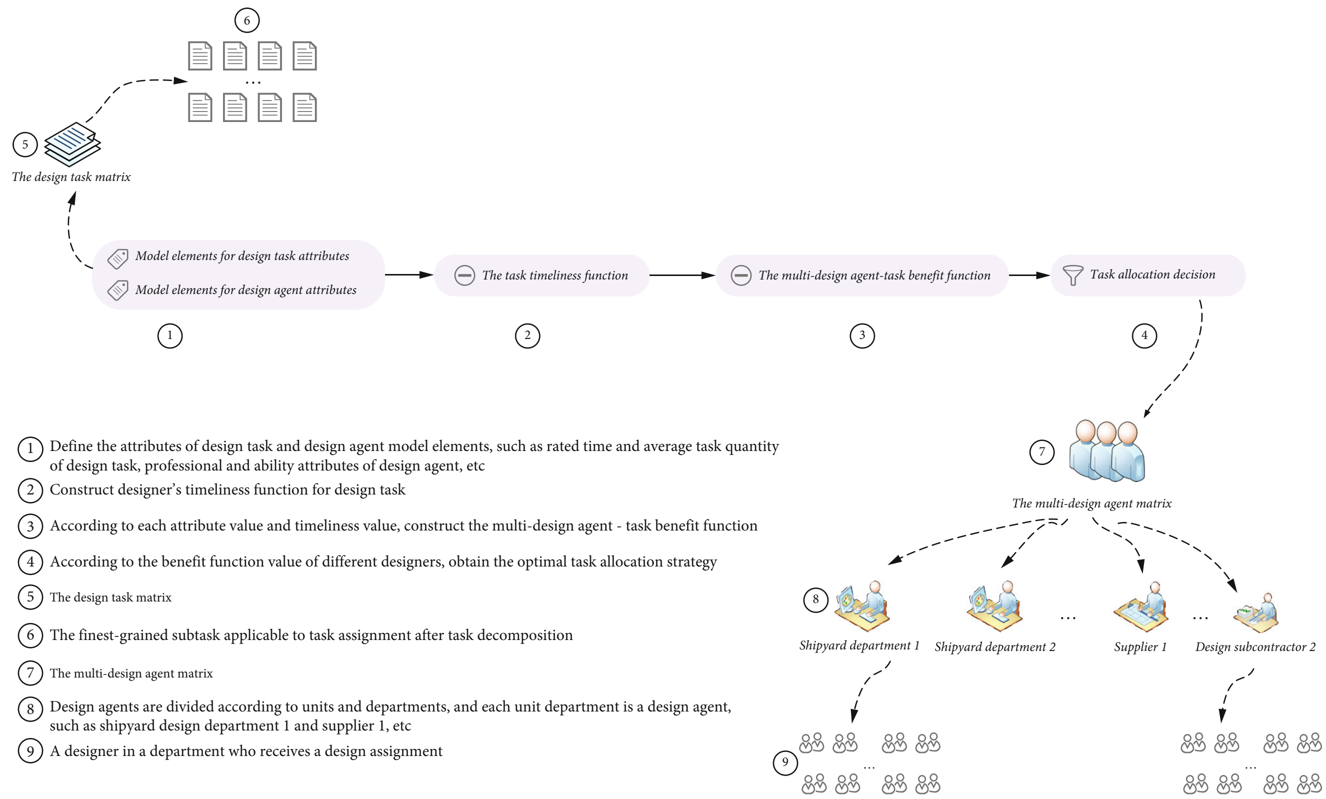

Figure 1: The decomposition logic diagram of the multidesign agent-task allocation decision-making method.

et al. [33] proposed a task allocation strategy that can capture complex interactions between tasks and personnel by constructing a personnel bias model that includes personnel bias, task basic facts, and character characteristics. Wei et al. [34] took the aircraft assembly coordination task and personnel balance as the background, comprehensively considered the factors such as task granularity, equalization degree, and personnel ability attribute, and constructed the task personnel evaluation matrix based on the fuzzy linguistic variable method. Huang et al. [35] constructed a time-dependent task assignment algorithm in the context of the task assignment problem for mobile groups with time constraints and considered the time-dependent task assignment problem with personnel time perception capability and perceived duration. Park et al. [36] studied the multirobot task allocation problem by applying cross-attentive machines to compute robot preferences for tasks and constructing deep reinforcement learning algorithms to solve the task optimal allocation time problem. Xu et al. [37] took the characteristics of the tasks, system features, and the randomness of personnel requirements and other attributes into account and constructed a multiobjective task scheduling model in the context of the cloud task assignment problem. Ji et al. [38] proposed an evolutionary multitasking allocation method with the goal of maximizing the perceived quality of the task while considering three types of constraint attributes: task budget, perceived quality of the task, and personnel workload. Zhao et al. [39] combined mobile crowdsourcing with social networks to consider the important influence of personnel relationship attributes in task assignment.

Therefore, a conclusion can be drawn from the literature: only by constructing a task allocation decision-making strategy on the basis of taking the bilateral attribute requirements of personnel and tasks into account can the subjective initiative of personnel be fully utilized and the balance of task allocation can be maximized. This paper analyzes the professional attributes, ability attributes, design efficiency, design rework rate, and personnel collaboration rate of ship collaborative designers. These attributes are a generalized concept, and the determination of their values is an uncertain problem. In order to qualitatively analyze its value, this paper first uses Delphi expert consultation method and empirical investigation method to determine the evaluation information of designers' ability attributes; Secondly, this paper uses the fuzzy linguistic variable method to quantify its value and get the capability attribute evaluation matrix through weight calculation.

Delphi expert consultation method and experience investigation method are both investigation methods that obtain a large number of actual data through various investigation methods, integrate and analyze the data with the knowledge and experience of experts, and finally obtain the characteristics of the research object. This paper combines Delphi expert consultation method and experience investigation method, through the investigation, analysis and statistics of the completion time, quality, feedback of tasks, others' evaluation and other contents of the designers to complete the task, finally obtains the description information of the evaluation size of the ship designers' ability attributes. For example, for the collaborative ability of designers, the collaborative ability is described as follows: general synergy rate, higher synergy rate, and high synergy rate. Another example is to describe the attribute size of the designer's negotiation and communication ability, analysis and planning ability, and practice and execution ability as follows: poor, average, better, and very good.

The fuzzy linguistic variable method is applied to the problems that cannot be evaluated with accurate numerical values in the decision-making process. The semantics of elements in a fuzzy linguistic set are usually represented by fuzzy numbers defined on [0,1]. The capability attribute information fuzzy set with three description elements is represented by a triangular fuzzy number, and the capability attribute information fuzzy set with four description elements is represented by a trapezoidal fuzzy number. For example, the designer collaboration rate is quantified as (0.5, 0.75, 1), and the negotiation and communication ability of designers is quantified as (0.25, 0.5, 0.75, 1). Finally, the ability attribute evaluation matrix is obtained by calculating the weight. At the same time, the fuzzy linguistic variable method is used to construct the task quantity evaluation matrix. Fuzzy decision-making method can be applied to the selection and evaluation of various fields. Hakim Nik Badrul Alam et al. [40] proposed a novel multicriteria decision-making (MCDM) model based on IZN and applied it to the selection of automobile suppliers. Venugopal et al. [41] constructed the fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach and applied it to the stock selection of investors and traders in the financial field. Imeni [42] believes that it is also very necessary to apply the fuzzy decision-making method to economic decisions such as accounting and auditing. Sirbiladze [43] introduced various operators used in fuzzy decision-making. Sorourkhah and Edalatpanah [44] also extended their research.

The ability attribute description of designers and its quantitative processing with fuzzy linguistic variables and the specific process of constructing the ability attribute matrix are shown below.

(1) Quantify Q_{Df}

For the design task T_{ij}, the professional attribute value of a single designer D_{pq} for the task ${}_p^q\widehat{Q}_{Df_i^j}$, the professional attribute size is described as follows: $\{$Professional mismatch, Major match, Professional match$\}$..

Through the Delphi expert consultation method and empirical survey method, the attribute evaluation set of the ability is summarized. The above description of the ability is fuzzy and uncertain and cannot be qualitatively analyzed, so it is quantified. The capacity of designers is reflected by specific numerical values. The quantized values of ${}_p^q\widehat{Q}_{Df_i^j}$ are as Table 2.

$$
{}_p^q\widehat{Q}_{Df_i^j} \in \{0, 0.5, 1\}. \tag{23}
$$

Designer selection strategy: avoid choosing designers who do not match the task's specialty, consider choosing designers who are more suitable for the task, and give priority to designers who match the task's specialty.

Table 2: Quantification of personnel professional match description.

	Property description		
	Professional mismatch	Major match	Professional match
Quantified value	0	0.5	1

(2)Quantitative analysis of Q_{Dgx}, Q_{Dgy}, and Q_{Dgz}

Among the many types of ability attributes, this paper selects representative three types of attributes that are also important to the task completion effect as the research points. The three types of ability attributes are as follows: negotiation and communication ability, analysis and planning ability, and practical execution ability. The ability attribute evaluation set is as Table 3.

To sum up, design the main body ability attribute matrix Q_{Dg}, and the values of the elements are as follows.

$$
\begin{cases} Q_{Dgx_p^q} \in \{0.25, 0.5, 0.75, 1\}, \\ Q_{Dgy_p^q} \in \{0.25, 0.5, 0.75, 1\}, \\ Q_{Dgz_p^q} \in \{0.25, 0.5, 0.75, 1\}. \end{cases} \tag{24}
$$

The larger the value, the better the designer's ability.
It is defined as follows:

$$
\begin{cases} N_{dgx}^{0.25}, N_{dgx}^{0.5}, N_{dgx}^{0.75}, N_{dgx}^{1} = \\ \text{the number of elements in the matrix } Q_{Dgx} \\ \text{with the value } 0.25, 0.5, 0.75, 1, \end{cases} \tag{25}
$$

$$
\begin{cases} N_{dgy}^{0.25}, N_{dgy}^{0.5}, N_{dgy}^{0.75}, N_{dgy}^{1} = \\ \text{the number of elements in the matrix } Q_{Dgy} \\ \text{with the value } 0.25, 0.5, 0.75, 1, \end{cases} \tag{26}
$$

$$
\begin{cases} N_{dgz}^{0.25}, N_{dgz}^{0.5}, N_{dgz}^{0.75}, N_{dgz}^{1} = \\ \text{the number of elements in the matrix } Q_{Dgz} \\ \text{with the value } 0.25, 0.5, 0.75, 1. \end{cases} \tag{27}
$$

For example, $N_{dgx}^{0.25}$ represents the number of attribute values with a value of 0.25 in the attribute matrix Q_{Dgx} of the negotiation and communication ability of the design agent.

In order to calculate the attribute weight of the design agent's ability, according to formulas (25)–(27), there are the following definitions.

Table 3: Personnel ability description quantitative table.

	Property description			
	Poor	General	Better	Very good
Quantified value	0.25	0.5	0.75	1

Table 4: Staff design efficiency description quantitative table.

	Property description			
	Very low rework rate	Low rework rate	Higher rework rate	High rework rate
Quantified value	0.05	0.1	0.15	0.2

$$\begin{cases} I(Q_{Dg}) = 1 - \dfrac{1}{kl}, \\ I(Q_{Dgx}) = \sum\limits_{t=0.25,0.5,0.75,1} \dfrac{N_{dgx}^t}{kl}\left(1 - \dfrac{N_{dgx}^t}{kl}\right), \\ I(Q_{Dgy}) = \sum\limits_{t=0.25,0.5,0.75,1} \dfrac{N_{dgy}^t}{kl}\left(1 - \dfrac{N_{dgy}^t}{kl}\right), \\ I(Q_{Dgz}) = \sum\limits_{t=0.25,0.5,0.75,1} \dfrac{N_{dgz}^t}{kl}\left(1 - \dfrac{N_{dgz}^t}{kl}\right). \end{cases} \tag{28}$$

Define the weight of each attribute of the evaluation matrix as $\bar{\omega}_{gx}$, $\bar{\omega}_{gy}$, and $\bar{\omega}_{gz}$. Then through the above calculation formula (28), the weight calculation formula can be obtained as follows.

$$\begin{cases} \bar{\omega}_{gx} = \dfrac{I(Q_{Dg}) - I(Q_{Dgx})}{3I(Q_{Dg}) - (I(Q_{Dgx}) + I(Q_{Dgy}) + I(Q_{Dgz}))} \\ \bar{\omega}_{gy} = \dfrac{I(Q_{Dg}) - I(Q_{Dgy})}{3I(Q_{Dg}) - (I(Q_{Dgx}) + I(Q_{Dgy}) + I(Q_{Dgz}))} \\ \bar{\omega}_{gz} = \dfrac{I(Q_{Dg}) - I(Q_{Dgz})}{3I(Q_{Dg}) - (I(Q_{Dgx}) + I(Q_{Dgy}) + I(Q_{Dgz}))} \end{cases} \tag{29}$$

In summary, according to formula (29), the calculation formula for the ability attribute matrix of the design agent can be obtained.

$$Q_{Dg} = \bar{\omega}_{gx} Q_{Dgx} + \bar{\omega}_{gy} Q_{Dgy} + \bar{\omega}_{gz} Q_{Dgz}. \tag{30}$$

Designer selection strategy: priority is given to selecting designers with high personnel ability attribute values to complete design tasks.

(3)Quantitative analysis Q_{D_l}

The design rework rate value $Q_{Dl_p^q}$ of the designer D_{pq} for the task is quantified as Table 4.

$$Q_{Dl_p^q} \in \{0.05, 0.1, 0.15, 0.2\}. \tag{31}$$

Designer selection strategy: prioritize designers with extremely low rework rates or low rework rates, and avoid designers with high rework rates.

(4)Quantitative analysis of Q_{Dh} and Q_{Do}

The design efficiency value $Q_{Dh_p^q}$ of the designer D_{pq} for the task is quantified as Table 5.

$$Q_{Dh_p^q} \in \{0.5, 0.75, 1\}. \tag{32}$$

For the designer D_{pq}, the synergy rate value $Q_{Do_p^q}$ is quantified as Table 6.

$$Q_{Do_p^q} \in \{0.5, 0.75, 1\}. \tag{33}$$

Define the timeliness evaluation matrix Q_{Dho} as follows.

$$Q_{Dho} = \left[Q_{Dho_p^q}\right]_{k\times l}, \tag{34}$$

$$\{N_{dh}^{0.5}, N_{dh}^{0.75}, N_{dh}^{1} = \text{the number of elements in the matrix } Q_{Dh} \text{ with the value } 0.5, 0.75, 1, \tag{35}$$

$$\{N_{do}^{0.5}, N_{do}^{0.75}, N_{do}^{1} = \text{the number of elements in the matrix } Q_{Do} \text{ with the value } 0.5, 0.75, 1, \tag{36}$$

$$\begin{cases} I(Q_{Dho}) = 1 - \dfrac{1}{kl}, \\ I(Q_{Dh}) = \sum\limits_{t=0.5,0.75,1} \dfrac{N_{dh}^t}{kl}\left(1 - \dfrac{N_{dh}^t}{kl}\right), \\ I(Q_{Do}) = \sum\limits_{t=0.5,0.75,1} \dfrac{N_{do}^t}{kl}\left(1 - \dfrac{N_{do}^t}{kl}\right). \end{cases} \tag{37}$$

Table 5: Staff design efficiency description quantitative table.

	Property description		
	Average efficiency	Higher efficiency	High efficiency
Quantified value	0.5	0.75	1

Table 6: Personnel collaboration rate description quantitative table.

	Property description		
	General synergy rate	Higher synergy rate	High synergy rate
Quantified value	0.5	0.75	1

Define the weight of each attribute of the timeliness evaluation matrix as $\bar{\omega}_{dh}$, $\bar{\omega}_{do}$. According to formulas (35)–(37), the following formulas can be obtained.

$$\begin{cases} \bar{\omega}_{dh} = \dfrac{I(Q_{Dho}) - I(Q_{Dh})}{2I(Q_{Dho}) - (I(Q_{Dh}) + I(Q_{Do}))}, \\ \bar{\omega}_{do} = \dfrac{I(Q_{Dho}) - I(Q_{Do})}{2I(Q_{Dho}) - (I(Q_{Dh}) + I(Q_{Do}))}. \end{cases} \tag{38}$$

In summary, according to formula (38), the calculation formula of the timeliness evaluation matrix of the main body of the design can be obtained.

$$Q_{Dho} = \bar{\omega}_{dh} * Q_{Dh} + \bar{\omega}_{do} * Q_{Do}. \tag{39}$$

3.2. Construct Task Timeliness Function. Define the timeliness function of the designer D_{pq} to the design task T_{ij} as U_{ij}^{pq}. According to formulas (12) and (39), the following formulas can be obtained.

$$U_{ij}^{pq} = \sqrt{1 + \lambda * q_{te_i^j} * Q_{Dho_p^q}}. \tag{40}$$

In the formula, λ is the time-dependent coefficient, $\lambda \in (0, 1)$. The greater the timeliness coefficient, the more timeliness of completion of the tasks of designers with the higher design efficiency and collaboration rate under the same task conditions. For different designers, the task timeliness function values are different. The higher the weight of designer efficiency and collaboration rate, the stronger the task timeliness.

3.3. Construct Multidesign Agent-Task Benefit Function.
(1)Task capacity evaluation matrix

There are many professions involved in ship collaborative design tasks. This article takes the three majors of structure $\tilde{A}$, piping $\tilde{B}$, and electrical $\tilde{C}$ as examples.

$$\begin{cases} NT_i^{\tau} = \text{number of tasks with type } \tau \text{ in set } T_i, \\ \tau \in \left\{\tilde{A}, \tilde{B}, \tilde{C}\right\}, \\ 1 \le i \le m. \end{cases} \tag{41}$$

$$m\tilde{A} = \sum_{i=1}^{m} NT_i^{\tilde{A}}, m\tilde{B} = \sum_{i=1}^{m} NT_i^{\tilde{B}}, m\tilde{C} = \sum_{i=1}^{m} NT_i^{\tilde{C}}, \tag{42}$$

$$m\tilde{A} + m\tilde{B} + m\tilde{C} = m * n, \tag{43}$$

$$\begin{gathered} \tilde{M}\tilde{A} = \left[\frac{NT_1^{\tilde{A}}}{m\tilde{A}}, \frac{NT_2^{\tilde{A}}}{m\tilde{A}}, \cdots, \frac{NT_m^{\tilde{A}}}{m\tilde{A}}\right], \tilde{M}\tilde{B} = \left[\frac{NT_1^{\tilde{B}}}{m\tilde{B}}, \frac{NT_2^{\tilde{B}}}{m\tilde{B}}, \cdots, \frac{NT_m^{\tilde{B}}}{m\tilde{B}}\right] \\ \tilde{M}\tilde{C} = \left[\frac{NT_1^{\tilde{C}}}{m\tilde{C}}, \frac{NT_2^{\tilde{C}}}{m\tilde{C}}, \cdots, \frac{NT_m^{\tilde{C}}}{m\tilde{C}}\right]. \end{gathered} \tag{44}$$

Among them, $NT_i^{\tilde{A}}$ represents the number of structure $\tilde{A}$ tasks in the task item T_i, $m\tilde{A}$ represents the number of structure $\tilde{A}$ tasks in all tasks, $NT_i^{\tilde{A}}/m\tilde{A}$ represents the ratio of the number of tasks of structure $\tilde{A}$ in the subtask T_i to the number of tasks of structure $\tilde{A}$ in all tasks. The other matrix elements are similar. According to formulas (41)–(44), the following formulas can be obtained.

$$I\left(\tilde{M}\right) = 1 - \frac{1}{m}, \tag{45}$$

$$\begin{cases} I\left(\tilde{M}\tilde{A}\right) = \sum_{i=1}^{m} \dfrac{NT_i^{\tilde{A}}}{m}\left(1 - \dfrac{NT_i^{\tilde{A}}}{m}\right), I\left(\tilde{M}\tilde{B}\right) = \sum_{i=1}^{m} \dfrac{NT_i^{\tilde{B}}}{m}\left(1 - \dfrac{NT_i^{\tilde{B}}}{m}\right) \\ I\left(\tilde{M}\tilde{C}\right) = \sum_{i=1}^{m} \dfrac{NT_i^{\tilde{C}}}{m}\left(1 - \dfrac{NT_i^{\tilde{C}}}{m}\right). \end{cases} \tag{46}$$

Define the weight of each attribute of the task load evaluation matrix as $\bar{\omega}_{\tilde{M}\tilde{A}}, \bar{\omega}_{\tilde{M}\tilde{B}}$, and $\bar{\omega}_{\tilde{M}\tilde{C}}$. Then, through the above calculation, formulas (45) and (46), the weight calculation formula can be obtained as follows.

$$\begin{cases} \bar{\omega}_{\tilde{M}\tilde{A}} = \dfrac{I\left(\tilde{M}\right) - I\left(\tilde{M}\tilde{A}\right)}{3I\left(\tilde{M}\right) - \left(I\left(\tilde{M}\tilde{A}\right) + I\left(\tilde{M}\tilde{B}\right) + I\left(\tilde{M}\tilde{C}\right)\right)}, \\ \bar{\omega}_{\tilde{M}\tilde{B}} = \dfrac{I\left(\tilde{M}\right) - I\left(\tilde{M}\tilde{B}\right)}{3I\left(\tilde{M}\right) - \left(I\left(\tilde{M}\tilde{A}\right) + I\left(\tilde{M}\tilde{B}\right) + I\left(\tilde{M}\tilde{C}\right)\right)}, \\ \bar{\omega}_{\tilde{M}\tilde{C}} = \dfrac{I\left(\tilde{M}\right) - I\left(\tilde{M}\tilde{C}\right)}{3I\left(\tilde{M}\right) - \left(I\left(\tilde{M}\tilde{A}\right) + I\left(\tilde{M}\tilde{B}\right) + I\left(\tilde{M}\tilde{C}\right)\right)}. \end{cases} \tag{47}$$

It is defined as follows:

$$\Gamma = [\Gamma_1, \Gamma_2, \cdots, \Gamma_m], \tag{48}$$

$$\Gamma_i = \bar{\omega}_{\tilde{M}\tilde{A}} \tilde{M}\tilde{A}_i + \bar{\omega}_{\tilde{M}\tilde{B}} \tilde{M}\tilde{B}_i + \bar{\omega}_{\tilde{M}\tilde{C}} \tilde{M}\tilde{C}_i. \tag{49}$$

In summary, the task quantity evaluation matrix that defines the design task is Φ. According to formulas (11) and (49), the following formulas can be obtained.

Table 7: Design task.

Task item	Subtasks (professional classification)				
	1	2	3	4	5
1	Structure 1	Structure 1	structure2	Pipe system 3	Electrical 1
2	Structure 1	Pipe system 2	Electrical 2	Pipe system 1	Electrical 1
3	Structure 1	Structure 2	Pipe system 1	Pipe system 2	Electrical 3
4	Structure 3	Pipe system 3	Pipe system 3	Electrical 2	Electrical 3

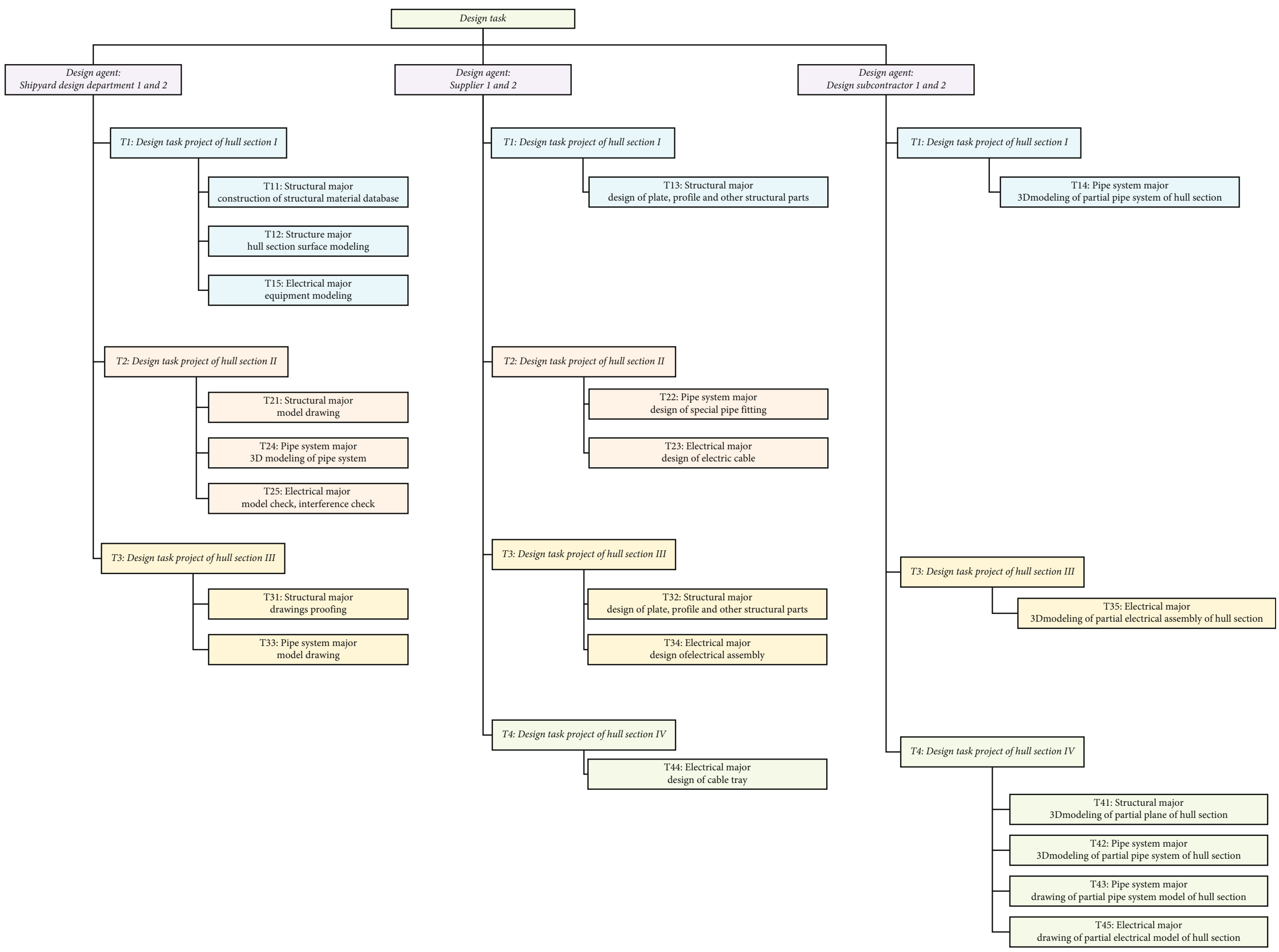

Figure 2: Task item decomposition and specific contents of subtasks.

$$\Phi = \left[\Gamma_i Q_{TE_i^j}\right]_{m\times n}. \tag{50}$$

(2)Construct multidesign agent-task benefit function

Taking a single task T_{ij} as an example, the T_{ij} benefit function of selecting the designer D_{pq} is defined as V_{ij}^{pq}. According to formulas (30), (40), and (50) and the relevant attribute values ${}_p^q\widehat{Q}_{Df_i^j}$ and $Q_{Dl_p^q}$ of the designer, the following formulas can be obtained.

Table 8: Design task-number of rated personnel.

Task item	Subtasks (number of rated personnel)				
	1	2	3	4	5
1	2	1	1	2	2
2	1	1	2	2	1
3	3	1	1	2	1
4	2	2	1	2	2

Table 9: Design task-rated completion time.

Task item	Subtasks (rated completion time)				
	1	2	3	4	5
1	10	6	5	12	8
2	8	5	6	8	8
3	15	4	5	10	6
4	12	8	4	8	8

Table 10: Design task-average task amount.

Task item	Subtasks (average task amount)				
	1	2	3	4	5
1	5	6	5	6	4
2	8	5	3	4	8
3	5	4	5	5	6
4	6	4	4	4	4

$$\begin{cases} V_{ij}^{pq} = \dfrac{{}_p^q\widehat{Q}_{Df_i^j} * U_{ij}^{pq} * \left[\theta * Q_{Dg_p^q} - (1-\theta) * Q_{Dl_p^q}\right]}{\Gamma_i Q_{TE_i^j}}, \\ i = 1, 2, \cdots, m \quad j = 1, 2, \cdots, n, \\ p = 1, 2, \cdots, k \quad q = 1, 2, \cdots, l. \end{cases} \tag{51}$$

Among them, θ is the designer's evaluation weight, $\theta \epsilon [0, 1]$. The larger the value, the greater the impact of designers' negotiation and communication ability, analysis and planning ability, and practical execution ability on task allocation in the benefit function. The benefit value calculated by the above formula, the larger the value, the better the selection strategy.

(3)Expected completion time of the task

Define the expected completion time of the subtask T_{ij} as t_{ij}: it indicates the expected time required for the assigned designer to complete the subtask after the designer assigns the task.

Define the average attribute value Q of designers: it means the ability attribute value $Q_{Dg_p^q}$ of all designers, the value of timeliness function $Q_{Dho_p^q}$, and the value of design rework rate $Q_{Dl_p^q}$.

$$Q = \frac{\sum_{p=1}^{k}\sum_{q=1}^{l} Q_{Dg_p^q} + \sum_{p=1}^{k}\sum_{q=1}^{l} Q_{Dho_p^q} - \sum_{p=1}^{k}\sum_{q=1}^{l} Q_{Dl_p^q}}{3 * k * l}. \tag{52}$$

Definition Π is the set of designers assigned to the subtask T_{ij}, and the size of Π is $Q_{TA_i^j}$, that is, the rated number of personnel for the subtask T_{ij}.

The definition X_{ij} is the average value of the original attributes of the designer assigned to the subtask T_{ij}.

$$X_{ij} = \frac{\sum_{\Pi} Q_{Dgx_p^q} + \sum_{\Pi} Q_{Dgy_p^q} + \sum_{\Pi} Q_{Dgz_p^q} + \sum_{\Pi} Q_{Dh_p^q} + \sum_{\Pi} Q_{Do_p^q} - \sum_{\Pi} Q_{Dl_p^q}}{6 * Q_{TA_i^j}}. \tag{53}$$

In summary, the calculation formula for the expected completion time t_{ij} of the subtask T_{ij} is as follows.

$$t_{ij} = Q_{TC_i^j} - Q_{TC_i^j}\left(X_{ij} - Q\right). \tag{54}$$

Among them, $Q_{TC_i^j}$ represents the rated time required to complete the subtask T_{ij}.

4. Instance Verification

4.1. Multidesign Agent-Task Benefit Function Example Verification. Taking a certain stage of ship collaborative design as an example, the multiagent-task allocation strategy proposed in this paper is applied. This paper sets the design agent as shipyard department 1, shipyard department 2, supplier 1, supplier 2, design subcontractor 1, and design subcontractor 2.

It is stipulated that different subtasks are distinguished by professional classification in Table 7. This paper takes the three types of majors of structure, pipe system, and electrical as examples and distinguishes design tasks applicable to different design agents by 1, 2, and 3, 1 for shipyard departments, 2 for suppliers, and 3 for design subcontracting. For example, structure 1 represents the structural design tasks that can be assigned to the shipyard department, and the others are the same.

T_i represents a hull section design project, which includes various professional design tasks for multiple design agents. The ship design is different from the work in other fields such as the construction industry. The hull structure is complex, and there are many tasks such as three-dimensional (3D) model establishment, inspection, and drawing. At the same time, it is necessary to carry out interference, balance, and weight center of gravity inspection, so that the model structures of various disciplines do not collide, and the designed hull meets the requirements of stability and rigidity. In this paper, the typical tasks of each major in hull sections I, II, III, and IV are selected for example analysis, that is, four task items are selected, and each task item contains five subtasks. The breakdown of task items and the specific content of subtasks are shown in Figure 2.

The rated number of personnel and the rated time of the design task are set as Tables 8–10.

This article selects six types of design agents, each of which contains four designers. These six design agents are shipyard department 1, shipyard department 2, supplier 1, supplier 2, design subcontractor 1, and design subcontractor 2. This article sets up the designer's ability attribute table, which contains the ability attribute values of the designer's negotiation and communication, analysis and planning, practice execution, design efficiency, collaboration rate, and design rework rate.

Table 11: Designer capability attribute.

Design agent	Designer	Capability attribute: Negotiation and communication	Analysis and planning	Practice execution	Design efficiency	Collaboration rate	Design rework rate
Shipyard department 1	1	0.75	0.5	0.75	1	0.75	0.05
	2	1	1	1	0.75	1	0.05
	3	0.5	1	0.75	1	1	0.15
	4	0.75	0.75	0.5	0.5	0.75	0.1
Shipyard department 2	1	1	1	0.75	0.75	0.5	0.1
	2	1	1	1	0.5	1	0.05
	3	0.75	0.75	0.75	0.75	0.75	0.1
	4	0.5	0.5	0.5	1	0.5	0.05
Supplier 1	1	0.25	1	1	1	1	0.15
	2	0.75	0.75	0.75	0.5	0.75	0.1
	3	0.75	1	1	1	1	0.05
	4	1	1	1	1	0.5	0.1
Supplier 2	1	1	1	1	0.75	0.75	0.1
	2	0.75	0.75	0.75	1	0.5	0.05
	3	0.5	0.75	0.5	0.5	1	0.1
	4	0.75	0.25	1	1	1	0.2
Design subcontractor 1	1	0.5	0.5	0.5	1	0.5	0.1
	2	1	1	1	0.75	0.75	0.05
	3	0.25	1	0.25	0.75	1	0.2
	4	1	0.5	1	1	1	0.05
Design subcontractor 2	1	1	1	1	1	1	0.1
	2	1	1	1	0.5	0.75	0.05
	3	0.75	0.75	0.75	1	0.5	0.1
	4	1	0.5	1	0.75	0.75	0.05

Table 12: Designer's ability attribute matrix-Q_{Dg}.

	Design agent	Designer (ability attribute matrix) 1	2	3	4
1	Shipyard department 1	0.663825758	1	0.760416667	0.661931818
2	Shipyard department 2	0.911931818	1	0.75	0.5
3	Supplier 1	0.772727273	0.75	0.924242424	1
4	Supplier 2	1	0.75	0.586174242	0.665719697
5	Design subcontractor 1	0.5	1	0.508522727	0.827651515
6	Design subcontractor 2	1	1	0.75	0.827651515

Table 13: Designer timeliness matrix-Q_{Dho}.

	Design agent	Designer (timeliness matrix) 1	2	3	4
1	Shipyard department 1	0.881081081	0.868918919	1	0.618918919
2	Shipyard department 2	0.631081081	0.737837838	0.75	0.762162162
3	Supplier 1	1	0.618918919	1	0.762162162
4	Supplier 2	0.75	0.762162162	0.737837838	1
5	Design subcontractor 1	0.762162162	0.75	0.868918919	1
6	Design subcontractor 2	1	0.618918919	0.762162162	0.75

The ability attribute description information of designers in each design agent is finally obtained through investigation, sorting, analysis, and statistics and combined with Delphi expert consultation method and experience investigation method. At the same time, according to the setting in Section 3.1, the description of capability attribute information corresponds to its semantic fuzzy number one by one. Finally, the ability attribute description information of each designer is quantized into Table 11 after numerical expression.

The designer's ability attribute matrix and timeliness matrix are calculated by formulas (30) and (39), as shown in Tables 12 and 13.

This article assumes that similar professions include different types of tasks such as drawing, modeling, review, and modification. However, because the specific content of the subtasks is different, the same designer has different professional attribute values for the subtasks of the same professional type. For example, the subtasks T_{11} and T_{12} belong to the structure 1 professional type, but the subtask T_{11} represents the construction of structural material database to the shipyard department, and the subtask T_{12} represents the structure professional modeling task applicable to the shipyard department. The professional attribute values of each subtask are different, and the others are the same.

Taking the assignment of the subtask T_{11} to the designer as an example, the designer's professional attribute value ${}_{p}^{q}\widehat{Q}_{Df_1^1}$ for the subtask T_{11} is set, and the benefit function is used to calculate the benefit function value of each designer for the subtask T_{11}. The details are shown in Table 14.

The timeliness coefficient $\lambda = 0.6$ in the benefit function formula and the personnel evaluation weight $\theta = 0.75$ are set. Through calculation, the designer's benefit function value V_{11}^{pq} for the subtask T_{11} can be obtained as follows. Through formula (51), the calculation results are shown in Table 15.

Based on the calculation result of the above benefit function and combined with the rated number of subtasks, designers D_{21} and D_{22} are finally assigned to subtask T_{11}.

After assigning a designer to the subtask T_{11}, the expected completion time is calculated by formulas (52)–(54):

$$\begin{aligned} Q &= \frac{36.3040}{3*6*4} = 0.5042, \\ X_{11} &= \frac{8.35}{6*2} = 0.6958, \\ t_{11} &= 10 - 10(0.6958 - 0.5042) = 8.08. \end{aligned} \tag{55}$$

It can be obtained that $t_{11} = 8.08$. Compared with its rated time, it can be seen that through the multidesigner-task allocation strategy proposed in this paper, the task time of ship collaborative design is reduced, the ability of designers is greatly utilized, and the matching degree between tasks and designers is improved.

In the same way, through the task allocation decision-making method for ship multiagent collaborative design proposed in this paper, other design tasks are allocated, and the task allocation strategy is shown in Table 16.

Table 14: Designer on subtask T_{11}-professional attribute-${}_{p}^{q}\widehat{Q}_{Df_1^1}$.

	Design agent	Designer (professional attribute matrix) 1	2	3	4
1	Shipyard department 1	1	0.5	1	0.5
2	Shipyard department 2	0.5	1	1	0.5
3	Supplier 1	0	0	0	0
4	Supplier 2	0	0	0	0
5	Design subcontractor 1	0	0	0	0
6	Design subcontractor 2	0	0	0	0

Table 15: Subtask T_{11}-designer benefit function value V_{11}^{pq}.

	Design agent	Designer (benefit function value) 1	2	3	4
1	Shipyard department 1	1.346	1.022	1.495	0.637
2	Shipyard department 2	0.891	2.016	1.471	0.497
3	Supplier 1	0	0	0	0
4	Supplier 2	0	0	0	0
5	Design subcontractor 1	0	0	0	0
6	Design subcontractor 2	0	0	0	0

Table 16: Design allocation strategy.

Task item	Subtasks (design allocation strategy) 1	2	3	4	5
1	D_{21}, D_{22}	D_{11}	D_{33}	D_{52}, D_{62}	D_{14}, D_{24}
2	D_{21}	D_{41}	D_{42}	D_{12}, D_{13}	D_{14}
3	D_{11}, D_{21}, D_{23}	D_{31}	D_{12}	D_{32}, D_{34}	D_{53}
4	D_{54}, D_{63}	D_{52}, D_{64}	D_{64}	D_{43}, D_{44}	D_{51}, D_{61}

Table 17: Expected completion time-t_{ij}.

Task item	Subtasks (expected completion time) 1	2	3	4	5
1	8.08	5.33	3.60	9.40	7.97
2	6.83	3.85	5.33	6.47	7.83
3	13.12	3.28	3.60	8.54	5.98
4	8.90	6.43	3.38	7.40	6.83

Based on the above task allocation strategy, the expected completion time of the task is calculated, and the results are shown in Table 17.

Comparing the rated completion time $Q_{TC_i^j}$ of the collaborative design task with the expected completion time t_{ij}, the analysis diagram is as Figure 3.

From the comparative analysis of the design task's rated completion time and the expected completion time, it can be seen that the use of the ship multidesign agent-task allocation

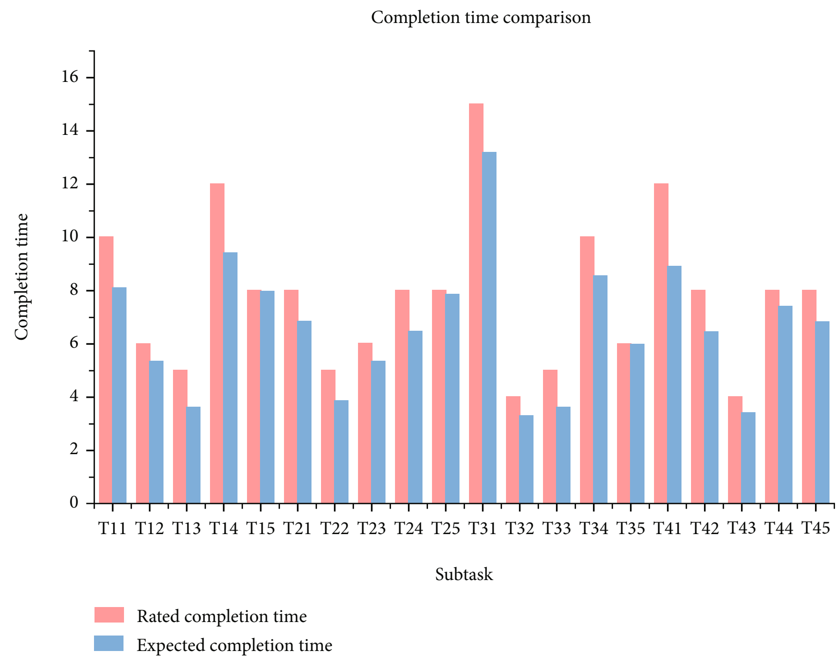

FIGURE 3: Completion time comparison chart.

TABLE 18: RR-design allocation strategy.

Task item	Subtasks (RR-design allocation strategy) 1	2	3	4	5
1	D_{11}, D_{12}	D_{12}	D_{31}	D_{51}, D_{63}	D_{11}, D_{13}
2	D_{14}	D_{32}	D_{33}, D_{43}	D_{13}, D_{21}	D_{22}
3	D_{14}, D_{21}, D_{23}	D_{34}	D_{24}	D_{41}, D_{44}	D_{52}
4	D_{53}, D_{64}	D_{51}, D_{54}	D_{61}	D_{31}, D_{42}	D_{52}, D_{62}

TABLE 19: RR-expected completion time.

Task item	Subtasks (RR-expected completion time) 1	2	3	4	5
1	8.04	4.33	4.10	11.50	6.83
2	7.83	4.69	5.10	6.70	6.10
3	13.65	3.08	5.06	8.21	Professional mismatch
4	11.05	7.13	2.75	6.83	Professional mismatch

TABLE 20: WRR-design allocation strategy.

Task item	Subtasks (WRR-design allocation strategy) 1	2	3	4	5
1	D_{12}, D_{13}	D_{21}	D_{34}	D_{51}, D_{63}	D_{12}, D_{13}
2	D_{22}	D_{41}	D_{31}, D_{43}	D_{14}, D_{21}	D_{24}
3	D_{11} D_{14}, D_{23}	D_{42}	D_{11}	D_{32}, D_{44}	D_{61}
4	D_{52}, D_{64}	D_{51}, D_{53}	D_{62}	D_{31}, D_{33}	D_{52}, D_{54}

TABLE 21: WRR-expected completion time.

Task item	Subtasks (WRR-expected completion time) 1	2	3	4	5
1	7.71	5.13	3.85	11.50	6.17
2	6.10	3.85	5.40	7.33	8.10
3	13.81	3.55	4.44	9.04	Professional mismatch
4	9.65	8.07	3.22	6.17	6.10

strategy proposed in this paper shortens the task completion time.

4.2. Algorithm Comparison Analysis. In order to verify the stability of the multidesign agent-task allocation decision-making method for ship collaborative design proposed in this paper, the Round-Robin (RR) algorithm and Weighted Round-Robin (WRR) algorithm are used as the experimental comparison objects. The RR and the WRR are applied to design task allocation, solve the corresponding task allocation strategy, and calculate the expected completion time of the task according to formula (54). By comparing the expected completion time of the task calculated by different methods, the stability of the proposed method, the RR, and the WRR in the task allocation problem is analyzed.

Both the RR and the WRR are a load balancing algorithm. The RR assumes that the processing performance of all servers is the same and allocates requests from users to internal servers in turn.

When the algorithm is applied to the task allocation problem, the RR is a task allocation method of stateless scheduling. This algorithm treats users as no difference and assigns tasks to users in turn in a Round-Robin manner.

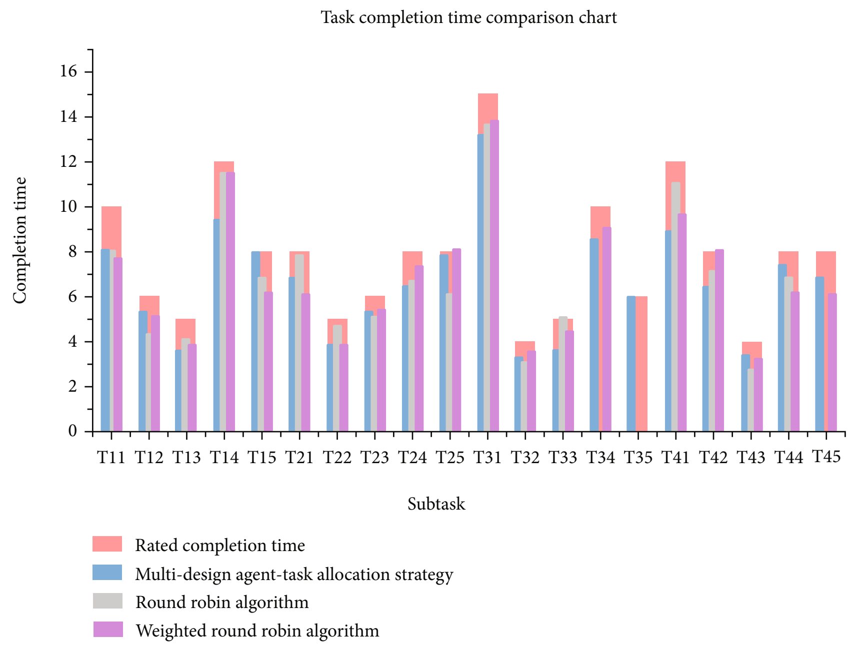

Figure 4: Task completion time comparison chart.

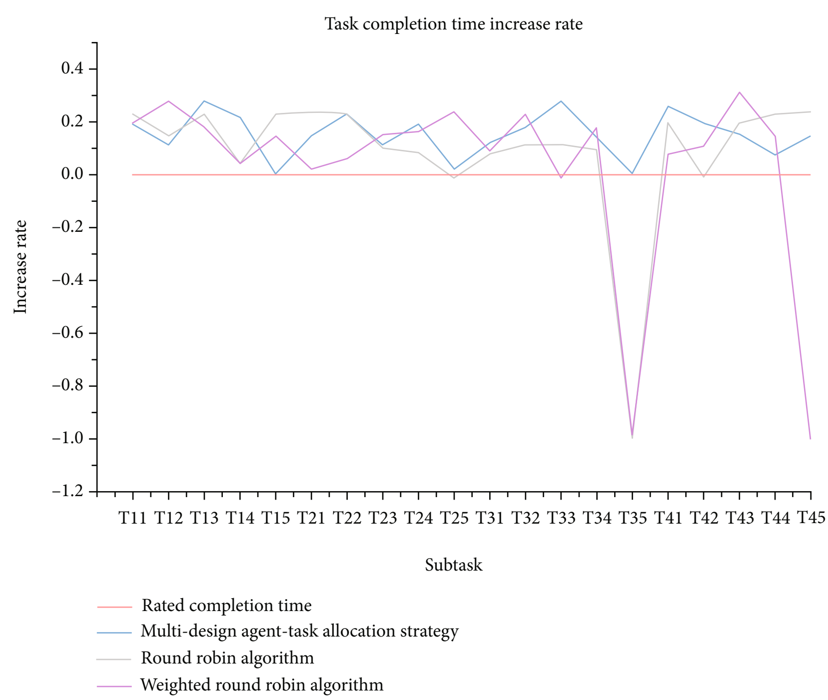

Figure 5: Task completion time increase rate chart.

Using the RR to calculate the task allocation strategy table and taking the corresponding professional attribute values of the personnel into account, the expected completion schedule of the calculation task is as Tables 18 and 19.

The WRR assigns different weights to each server according to the different processing capabilities of the server, so that it can accept service requests with corresponding weights. When the algorithm is applied to the task allocation problem, the rated number of tasks completed is used as the weight, so that the task can be allocated to the designer of the specified number of completed tasks. The WRR is used to calculate the task allocation strategy table, and the corresponding

Table 22: Task allocation method stability.

	Task allocation method stability		
	Multidesign agent-task allocation decision-making method	RR	WRR
Stability value	100%	85%	85%

professional attribute values of the personnel are considered at the same time. The expected completion schedule of the task is as Tables 20 and 21.

The expected completion time of tasks calculated by the multidesign agent-task allocation decision-making method and the RR and the WRR are compared. The comparison and analysis diagram is as Figure 4.

Comparing the multidesign agent-task allocation decision-making method and the RR and the WRR proposed in this paper, the designer's task completion time increase rate is calculated, and the comparison and analysis diagram is as Figure 5.

The stability values of the three task allocation methods are shown in Table 22.

Through the above analysis, the multidesign agent-task allocation decision-making method proposed in this paper has advantages in the balance and stability of task and personnel allocation. The specific advantages are as follows.

(i) The multidesign agent-task allocation decision-making method fully considers the task attributes of the task, the professional attributes of the personnel, the ability attributes, the design rework rate, and other character attributes and can take the bilateral needs of the task and the personnel into account at the same time. The RR and the WRR do not consider the attributes of tasks and personnel when assigning tasks and treat all objects as indistinguishable

(ii) The task-agent allocation strategy obtained by applying the multidesign agent-task allocation decision-making method improves the designer's task completion efficiency and reduces the task completion time. With the task allocation strategy solved by the RR and the WRR, there is a mismatch between the task and the designer's profession, which makes the designer unable to complete the task. The stability of these two algorithms is significantly lower than that of the multidesign agent-task allocation decision-making method

(iii) Comprehensive analysis shows that the multidesign agent-task allocation decision-making method proposed in this article has more advantages in terms of balance and stability of task and designer allocation, makes full use of design resources, and is more in line with the current situation of multispecialty parallelism in ship collaborative design. It is more in line with the task distribution requirements of ship collaborative design

5. Conclusion

This paper presents a multidesign agent-task allocation decision-making method for multidesign agents, which takes into account the task attributes and the ability attributes of designers. The purpose is to formulate a reasonable task allocation strategy for ship collaborative design, achieve resource balance, and improve design efficiency. This paper verifies the effectiveness, feasibility, and stability of the multidesign agent-task allocation decision-making method through the example verification analysis and the comparison analysis of RR and WRR algorithms.

The theoretical contributions of the multidesign agent-task allocation decision-making method are as follows: (1) This method expands the types of design agents in the task allocation process, considers the multiagent task recipients from different regions and units such as shipyards, suppliers, and design subcontractors, improves the flexibility and multiscalability of multidesign agents, and further deepens the concept of multiagent theory. (2) This method considers the task attribute, the specialty attribute, and the capability attribute of the design subject and constructs the task timeliness function and the multidesign subject task benefit function, so that designers with different specialties and abilities can coordinate and allocate based on the unified and reasonable theory, and further deepens the concept of collaboration in ship collaborative design. (3) In this method, Delphi expert consultation method and experience investigation method are used to determine the ability attribute evaluation information of designers. Secondly, fuzzy linguistic variable method is used to quantify its value, and the ability attribute evaluation matrix is obtained through weight calculation, which further expands the application method of personnel evaluation decision. The practical significance is as follows: (1) The enterprise decision-makers can make full use of and reasonably allocate resources by using the multidesign agent task allocation decision-making method to allocate tasks to the most appropriate executors, so that the task executors can complete the collaborative design tasks with high efficiency, low cost, and high quality and finally improve the design efficiency of collaborative design products and enhance the core competitiveness of enterprises. (2) The application of the multidesign agent-task allocation decision-making method satisfies the multidesign agent task benefit function and can simultaneously take into account the bilateral needs of tasks and personnel. It is helpful for shipyards, suppliers, design subcontractors, and other enterprises to participate in the project management and personnel management of ship collaborative design.

It is a very complicated work to balance the assignment of tasks and personnel in ship collaborative design. This paper selects and studies several typical representatives of design agent attributes that need to be considered in task assignment. At the same time, it is set that the assigned design tasks have reached the most fine-grained for task assignment. In addition to the task attributes and personnel attributes set in this paper, there are many factors that affect the task designer allocation strategy, such as task decomposition granularity, task context, and designer reward and punishment mechanism. In future research, we will refine the personnel attributes that affect the task allocation strategy, consider the impact of personnel reward and punishment measures on the ability of designers to perform tasks, further explore the impact of fine-grained task decomposition on task allocation, and continue to expand the collaborative design task scheduling strategy of shipyards, suppliers, design subcontractors, and other multidesign agents.

Data Availability

All data, models, and code generated or used during the study appear in the submitted article.

Disclosure

The authors are responsible for the contents of this publication.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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