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RESEARCH ARTICLE

Human-Machine Function Allocation Method Based on a Non-Cooperative Game for the Manned Submersible

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ABSTRACT The human-machine function allocation (HFA) strategy of manned submersibles is an important factor that affects the reliability of oceanauts. However, the uncertainty of the HFA strategy makes its optimization very complicated. To this end, a non-cooperative game-based HFA method is proposed, which transforms the multi-objective optimization model of mental workload and situation awareness (SA) under the allocation strategy into a non-cooperative game model and forms a mapping relationship. Mental workload and situation awareness are used as non-cooperative game players. Assignable functions are attributed to the players by fuzzy clustering analysis and combined with non-assignable functions to construct the utility matrix by utility functions. The optimal allocation strategy combination is obtained through the Nash equilibrium analysis of the utility matrix. The proposed method was applied to the optimization of the HFA strategy of the manned submersible during the navigation.

INDEX TERMS Human-machine function allocation (HFA), mental workload, situation awareness (SA), SAGAT, VACP.

I. INTRODUCTION

As the core of the human-machine-environment system in the manned submersible, oceanauts are responsible for the important tasks of submersible driving and operation [1]. When oceanauts are under high mental workload or low situation awareness for a long time, it will greatly increase the probability of oceanauts making wrong decisions during the mission [2]. Therefore, it has become one of the key issues to rationalize the HFA strategy for manned submersibles according to the working characteristics of oceanauts.

Single-objective optimization improves the human reliability in function allocation, but it cannot adapt to the multi-objective conflicts in actual function allocation [3], [4], [5], [6]. Functional models consider multiple-objective conflicts, but they are unable to perform quantitative calculations [7], [8]. Bayesian networks (BNs) and weighted evaluation functions can characterize the mutual coupling between multiple optimization objectives, but BNs' root variables states, the weights of TOPSIS and linear weighted methods, and the resolution coefficient of grey correlation degree method are subjectively determined, so the optimization scheme will be with subjectivity and instability [9], [10], [11], [12].

Here, an HFA method based on a non-cooperative game is proposed for the manned submersible, which can objectively deal with the multi-objective conflict problem of HFA. Specifically, considering the human reliability requirements

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of manned submersible operations, the mental workload and situation awareness are considered as two players. Then the utility matrix is formed through the mental workload function, situation awareness function, and strategy spaces of two players. Finally, the Nash equilibrium point is found by analyzing and comparing the utility matrix to obtain the optimal HFA strategy.

II. MAPPING RELATIONSHIP

Multi-objective optimization problems are widespread in engineering applications and other fields. It can be described as an optimization problem consisting of a set of design variable parameters X, objective functions $F(X)$ and constraints $H(X)$, where design variables, objective functions, and constraints are functionally related to each other.

The multi-objective optimization problem is similar to the game decision problem in nature. If the existing method is used to solve the multi-objective optimization problem, the solution results will lack objectivity and have instability, but the multi-objective optimization problem can be transformed into a game decision problem to avoid the above defects. To transform the multi-objective optimization problem into a game decision problem, the mathematical model of the multi-objective optimization problem needs to be transformed into a non-cooperative game model, as shown in Fig. 1.

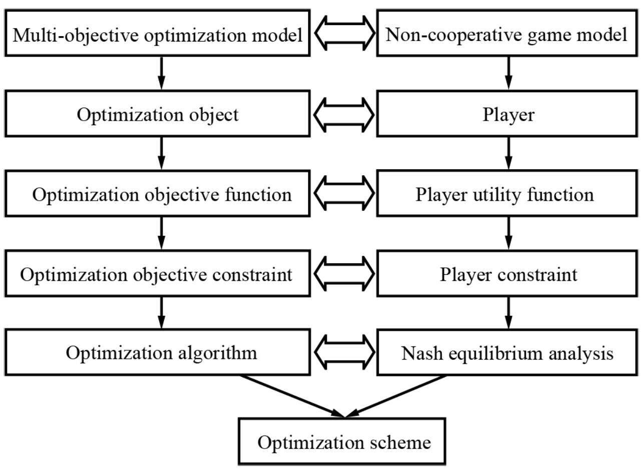

FIGURE 1. The mapping relationship between the multi-objective optimization model and non-cooperative game model.

When optimizing the HFA strategy for the manned submersible, different combinations of allocation strategies will lead to different mental workload and situation awareness. There is no consistent relationship between mental workload and situation awareness [13], [14]. Maintaining lower mental workload and higher situation awareness contributes to oceanauts' reliability. Based on this, this paper optimizes the HFA strategy with mental workload and situation awareness as the optimization objectives. The mathematical model of multi-objective optimization is shown in (1) and (2).

$$\begin{cases} \min W = W\left(W_1, W_2, \cdots, W_n\right) \\ \max SA = SA\left(SA_1, SA_2, \cdots, SA_n\right) \end{cases} \tag{1}$$

$$\begin{aligned} s.t. W_i &\in \left\{W_i'\right\} \\ SA_i &\in \left\{SA_i'\right\} \; 1 \leq i \leq n \\ W_{\max} &\leq |W_{\max}| \\ SA_{\min} &\geq |SA_{\min}| \end{aligned} \tag{2}$$

where W and SA are the mental workload function and situation awareness function, respectively; W_i' and SA_i' are the sets of mental workload and situation awareness for different allocation strategies of the function i, respectively; n is the number of functions for the manned submersible in a working process; $|W_{\max}|$ is the specified maximum safety threshold of mental workload for the manned submersible; $|SA_{\min}|$ is the specified minimum safety threshold of situation awareness for the manned submersible.

III. OPTIMIZATION MODEL

The non-cooperative game model can be expressed as $G = \{P_i; S_i; u_i\ (i = 1, 2, \cdots, n)\}$, where P_i is the player, S_i is the strategy space corresponding to the player P_i, and u_i is the utility function of the player [15]. In this paper, the players are mental workload and situation awareness. The strategy space consists of different combinations of allocation strategies for assignable functions which are attributed to the player. The utility is the benefits of the players.

In the non-cooperative game, each player maximizes its benefit within its strategy set and finally reaches the Nash equilibrium to obtain the optimal strategy. At this time, if the strategy of any player deviates from the Nash equilibrium, its own benefit will not increase. Therefore, the player will not make a strategy change alone to reduce its benefit, and the game will enter a stable state. The non-cooperative game model satisfies (3) at the Nash equilibrium point

$$u_i\left(s_i^*, s_{-i}^*\right) \geq u_i\left(s_i, s_{-i}^*\right) s_i \in S_i \tag{3}$$

where u_i is the utility of the player P_i; s_i^* is the strategy of the player P_i at the Nash equilibrium; s_{-i}^* is the strategy of other players except P_i at the Nash equilibrium; s_i is the strategy of the player P_i at the non-Nash equilibrium.

The 'self-imposed' nature of Nash equilibrium ensures a stable output solution without relying on subjective rules, resulting in remarkable objectivity and universality.

When using the non-cooperative game model for allocation strategy optimization, the HFA strategy is first analyzed for a working process of the manned submersible to establish a strategy layer. Secondly, in the game layer, assignable functions are attributed to the players by fuzzy clustering analysis. On this basis, the allocation strategy combinations consist of assignable functions and non-assignable functions. A multi-objective optimization model is then constructed with the objectives of mental workload function and situation awareness function to form a game utility matrix. Finally,

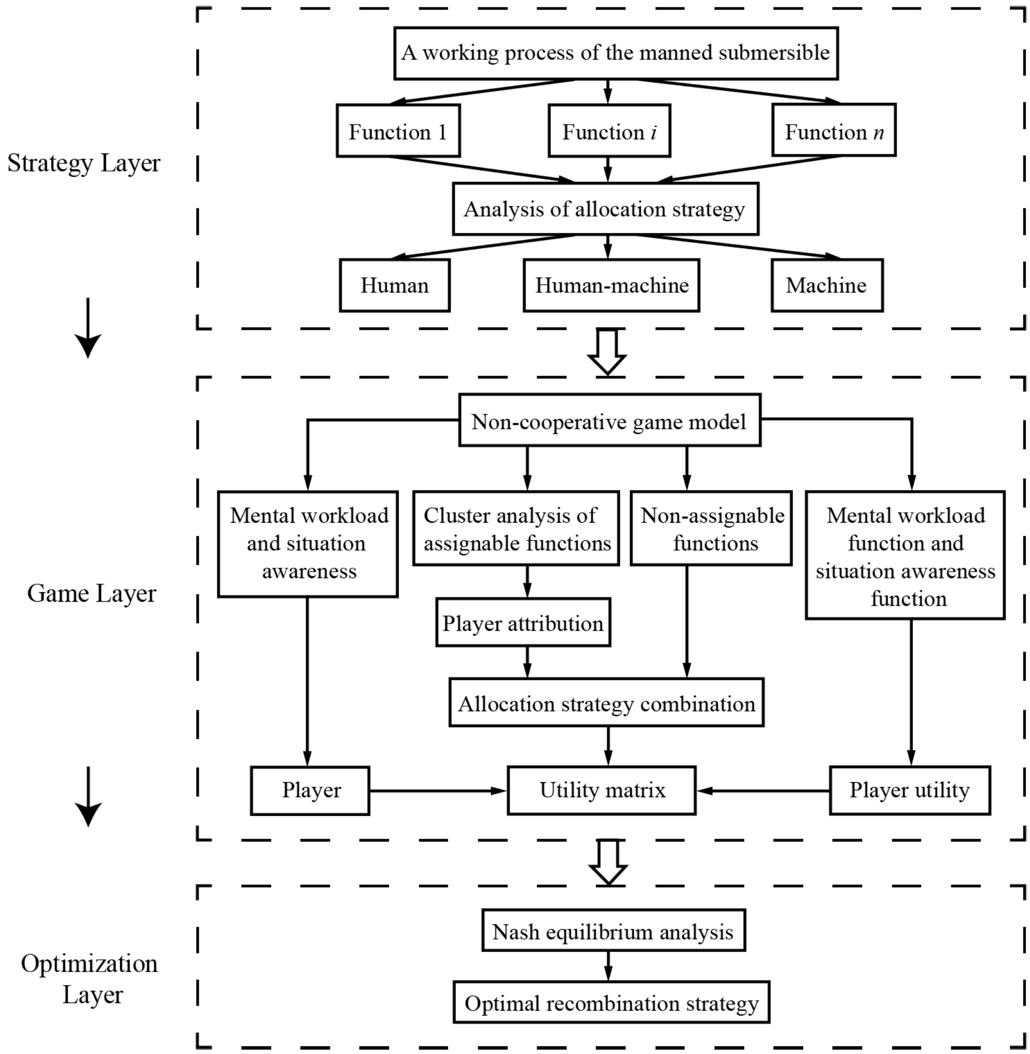

FIGURE 2. The HFA model based on a non-cooperative game.

in the optimization layer, the optimal allocation strategy is obtained by Nash equilibrium analysis of the game utility matrix. The whole process is shown in Fig. 2.

IV. METHOD

A. STRATEGY ANALYSIS

In a working process, a preliminary analysis of the functions involved is first required. According to Parasuraman's proposed types of human interaction with automation, human-machine functions are divided into four parts: information acquisition, information analysis, decision selection, and action implementation [16]. Next, the decision matrix for the function allocation is used to analyze the part that humans are good at, the part that machines are good at, or the part that both humans and machines are good at, where the factors judged can be accuracy, speed, reliability, etc. [17]. A function is assignable if it includes a part that both humans and machines are good at, and vice versa for a non-assignable function. Finally, the analysis of the automation level is performed on the parts of assignable functions that both humans and machines are good at performing to establish the allocation strategies of assignable functions [18].

B. PLAYER UTILITY FUNCTION

1) MENTAL WORKLOAD PLAYER

Given that this paper focuses on the HFA strategy as the research object, it is considered to directly link operational behavior with workload. Therefore, the VACP scale based on multiple resource theory is chosen for quantitative calculation of mental workload [19]. The VACP scale defines mental workload as four independent dimensions: visual, auditory, cognitive, and psychomotor. These dimensions can represent any operational behavior. The VACP scale has been validated in various fields, including aviation, medicine, and the military [20], [21], [22], and it is documented in the literature [23].

The execution process for a combination of HFA strategies can be decomposed into several subtasks, as shown in Fig. 3.

The load value of each subtask is determined by the VACP scale. The mental workload obtained from the VACP scale is an instantaneous value, so the average mental workload is chosen as the measure for combinations of HFA strategies based on the timeline dimension.

The utility function of the mental workload player is shown in (4) and (5)

$$W_t = \sum_{b=1}^{m} \sum_{a=1}^{n} W_{ab} \tag{4}$$

$$W = \frac{\sum_{t=1}^{n} W_t}{T} \tag{5}$$

where W_t is the value of mental workload at a moment t; W_{ab} is the value of mental workload for the subtask a in the channel b at a moment t; W is the average value of mental workload during the time period T.

2) SITUATION AWARENESS PLAYER

One of the freeze-probe techniques is the Situation Awareness Global Assessment Technique (SAGAT), which is a widely used objective measurement method with high sensitivity and reliability [24], [25]. Therefore, the SAGAT method is selected to measure situation awareness for different combinations of HFA strategies.

The SAGAT method requires subjects to perform target tasks in a simulated scene. The simulation experiment can be paused at any time to assess the subjects' perception (SA level 1), comprehension (SA level 2), and projection (SA level 3) of the elements in the simulated scene of the manned submersible by answering relevant questions.

To prevent subjects from shifting their attention to the information they know will be tested, a random sampling of all SA-related questions in the current environment is required [26]. The utility function of the situation awareness player is shown in (6) and (7)

$$SA_k = \frac{1}{n} \sum_{i=1}^{n} \sigma(i) \tag{6}$$

$$\sigma(x) = \begin{cases} 1, \textit{correct} \\ 0, \textit{wrong} \end{cases}$$

$$SA = \frac{\sum_{k=1}^{m} SA_k}{K} \tag{7}$$

where n is the number of questions and K is the number of subjects.

3) GAME UTILITY MATRIX

After confirming the players in the non-cooperative game model and their corresponding utility functions, the utility matrix can be constructed for different combinations of HFA strategies, as shown in Table 1.

The different allocation and combination strategies among assignable functions are common design variables for the mental workload function and the situation awareness function. The non-cooperative game model requires two players to make decisions independently and without interfering with each other, so it is necessary to attribute assignable functions to players to form the independent strategy spaces for both of them. The fuzzy clustering method can achieve flexible clustering of variables by adjusting the truncation value of the fuzzy similarity matrix. The process is as follows.

TABLE 1. Utility matrix for combinations of HFA strategies.

Combinations of HFA strategies	Mental workload utility u_1	Situation awareness utility u_2
X_1	$u_1(X_1)$	$u_2(X_1)$
X_2	$u_1(X_2)$	$u_2(X_2)$
$\vdots$	$\vdots$	$\vdots$
X_n	$u_1(X_n)$	$u_2(X_n)$

1) Establish initial samples. Single-objective optimization is performed on the player P_i to obtain its optimal combination of allocation strategies. Equation (4) and Equation (5) are used to calculate the mental workload occupied by each assignable function in the optimal strategy combination of mental workload. This calculation serves as the impact factor ξ_{iW} for each assignable function on the mental workload player. Several experts are selected to determine the relative impact of each assignable function on the situation awareness player using the Analytic Hierarchy Process (AHP) for the optimal strategy combination of situation awareness. The average value of the relative impact is taken as the impact factor ξ_{iSA} for each assignable function on the situation awareness player.

$$\zeta_i = \{\xi_{iW}, \xi_{iSA}\} \tag{8}$$

where ζ_i is a set of impact factors of assignable function i.

2) Treatment of the utility dimension. Since the utility dimensions of the two players are different, a dimensional treatment is required to eliminate the influence, as shown in (9)

$$\xi'_{ik} = \frac{\xi_{ik} - \bar{\xi}_k}{\sigma_k} i = 1, 2, \cdots, n \; k = W, SA \tag{9}$$

where $\bar{\xi}_k = \frac{1}{n} \sum_{i=1}^{n} \xi_{ik}$ and $\sigma_k = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\xi_{ik} - \bar{\xi}_k\right)^2}$.
After the range transformation, it is shown in (10)

$$\xi''_{ik} = \frac{\xi'_{ik} - \min\limits_{1 \le i \le n} \left\{\xi'_{ik}\right\}}{\max\limits_{1 \le i \le n} \left\{\xi'_{ik}\right\} - \min\limits_{1 \le i \le n} \left\{\xi'_{ik}\right\}} \tag{10}$$

3) Establish a fuzzy similar matrix. Establish the fuzzy similar matrix $R = \left(r_{ij}\right)_{n \times n}$, where r_{ij} is the similarity

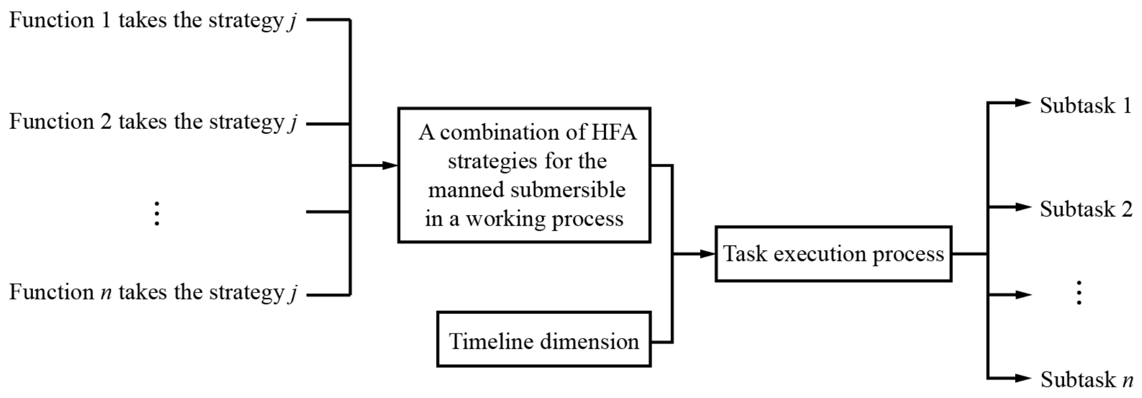

FIGURE 3. **Conversion relationship between functions and subtasks.**

between ξ''_{ik} and ξ''_{jk}, which is calculated by the absolute distance method, as shown in (11)

$$r_{ij} = \left\{ \begin{array}{cc} 1 & i = j \\ 1 - M \sum_{k} \left| \xi''_{ik} - \xi''_{jk} \right| & i \neq j \end{array} \right\} \tag{11}$$

where M is the similarity correction coefficient. The value of M should ensure that $r_{ij} \in [0, 1]$.

4) Establish a fuzzy equivalent matrix. The square self-synthesis method is used to construct the transitive closure matrix R^* for the fuzzy similar matrix R, which represents the fuzzy equivalent matrix of R and satisfies $R^* = R^* \circ R^*$. '$\circ$' is a Boolean operator.
5) Strategic clustering. The truncation λ is selected to classify the matrix according to the clustering requirements, and different cut sets are obtained when Equation (12) is satisfied. The attribution of assignable functions to players is realized by clustering the elements of the same cut set.

$$R^*_{\lambda} = \begin{cases} 1, r_{ij} \geq \lambda \\ 0, r_{ij} < \lambda \end{cases} \tag{12}$$

The utility matrix of the non-cooperative game model is finally obtained after completing the strategy clustering, as shown in Table 2.

4) SOLUTION OF NASH EQUILIBRIUM STRATEGY

In a non-cooperative game, when there is a strategy that gives all players strict advantages, it is the most stable result of the game. However, in practical engineering problems, the conflict between the utilities of players makes it difficult for the ideal strategy. The Nash equilibrium is a solution for such problems. Unlike the multi-objective method that coordinates the joint actions of all optimization objectives, the non-cooperative game allows each player to adjust only for their own benefits in a rational way. When each player selects the best strategy for themselves relative to other strategies, the game reaches Nash equilibrium. Combined with (3), the game reaches Nash equilibrium when the players satisfy (13) [27].

$$u_i \left(s^*_i, s^*_{-i} \right) = \min u_i \left(s_i, s^*_{-i} \right) \tag{13}$$

The algorithmic steps for the Nash equilibrium strategy in the non-cooperative game model are as follows:

1) Given strategy spaces, utility functions, constraints, and iteration accuracy ε.
2) Strategy sets belonging to players $S_1, S_2, \cdots, S_i, \cdots, S_m$ are obtained by fuzzy clustering.
3) The initialization of game analysis involves randomly generating the combination of initial feasible strategies $s^{(0)} = \left\{ s^{(0)}_1, s^{(0)}_2, \cdots, s^{(0)}_i, \cdots, s^{(0)}_m \right\}$ in strategy spaces $S = \{S_1, S_2, \cdots, S_i, \cdots, S_m\}$.
4) Denote $s^{(0)}_{-i}$ as the combination of initial feasible strategies taken by all players except $s^{(0)}_i$ in the combination of feasible initial strategies $s^{(0)}$, where $i = 1, 2, 3, \cdots, m$. The utility of each player $u_1(s), u_2(s), \cdots, u_i(s), \cdots, u_m(s)$ is used as the optimization objective. The single-objective optimization is performed in the strategy set of each player $S_1, S_2, \cdots, S_i, \cdots, S_m$, while keeping $s^{(0)}_{-i}$ constant. For any player i, the optimal strategy s^*_i is found in its corresponding strategy set S_i to satisfy the game utility $u_i \left(s^*_i, s^{(0)}_{-i} \right) \rightarrow \min$ and the constraint $h_k \left(s^*_i, s^{(0)}_{-i} \right) \leq 0$, where $k = 1, 2, \cdots, q$.
5) Let $s^{(1)} = s^*_1 \cup s^*_2 \cup \cdots \cup s^*_i \cup \cdots \cup s^*_m$, and then calculate whether the distance (the norm of the matrix) between two combinations of strategies $s^{(0)}$ and $s^{(1)}$ satisfies the convergence criterion $\left\| s^{(1)} - s^{(0)} \right\| \leq \varepsilon$ (ε is an arbitrarily small positive number). If it is satisfied, the game ends; if not, $s^{(0)}$ is replaced by $s^{(1)}$, and we return to step 3 for loop calculation until the accuracy requirement is met.

The block diagram for solving the Nash equilibrium strategy of the non-cooperative game model is shown in Fig. 4.

V. CASE STUDY

A. STRATEGY ANALYSIS

The main operation process of oceanauts in the manned submersible includes laying, diving, long-distance navigation, sample collection, and surfacing. This paper uses the

TABLE 2. Utility matrix of the non-cooperative game model.

	Situation awareness P_2		
Mental workload P_1	β_1	$\cdots$	β_m
α_1	$u_1(\alpha_1,\beta_1,\varphi_z), u_2(\alpha_1,\beta_1,\varphi_z)$	$\cdots$	$u_1(\alpha_1,\beta_m,\varphi_z), u_2(\alpha_1,\beta_m,\varphi_z)$
$\vdots$	$\vdots$		$\vdots$
α_n	$u_1(\alpha_n,\beta_1,\varphi_z), u_2(\alpha_n,\beta_1,\varphi_z)$	$\cdots$	$u_1(\alpha_n,\beta_m,\varphi_z), u_2(\alpha_n,\beta_m,\varphi_z)$

The utility $u_1(\alpha_n,\beta_m,\varphi_z)$ and utility $u_2(\alpha_n,\beta_m,\varphi_z)$ are respectively the utility of the mental workload player and the utility of the situation awareness player when the assignable functions belonging to the player P_1 use the combination of strategies n, the assignable functions belonging to the player P_2 use the combination of strategies m, and the non-assignable functions use the fixed combination of strategies z.

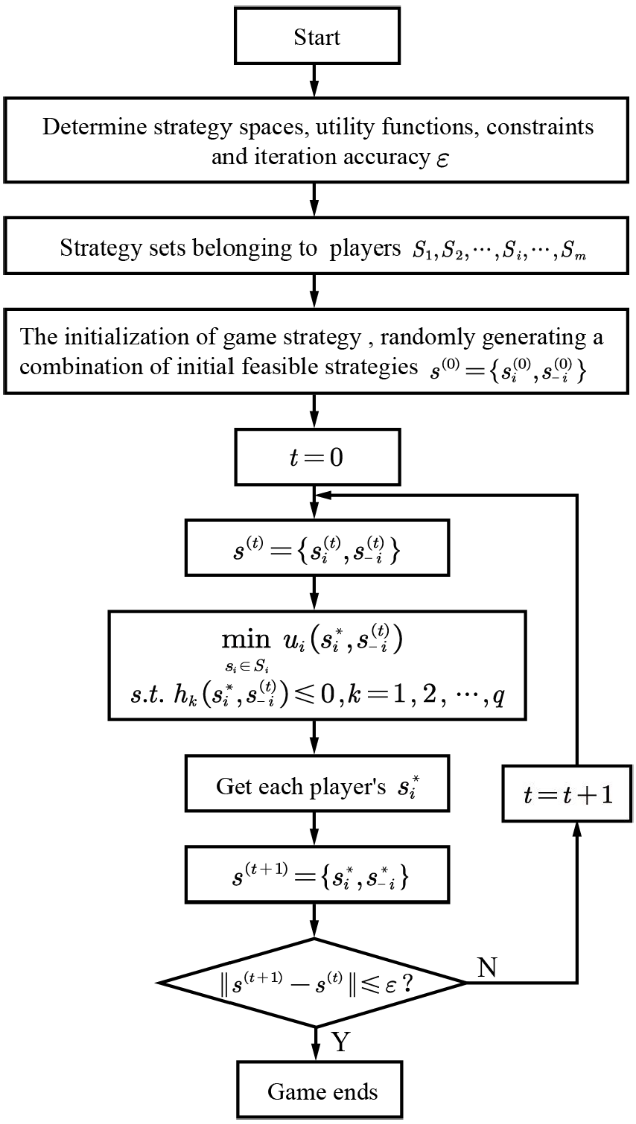

FIGURE 4. The block diagram for solving the Nash equilibrium strategy.

navigation process of the manned submersible as a case study. The functions involved in the navigation process of the manned submersible include communication, detection, navigation, life support, thruster monitoring, collision avoidance,

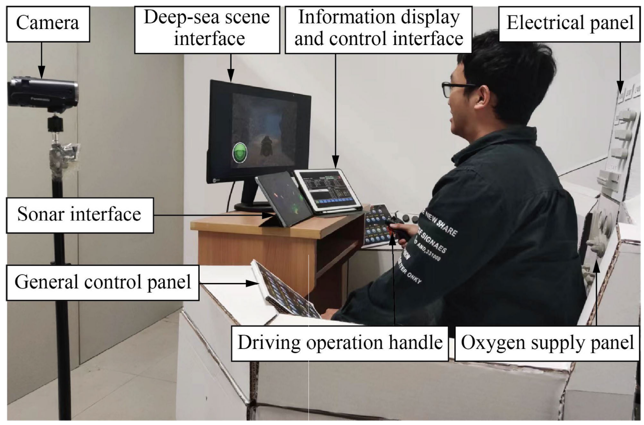

FIGURE 5. The manned submersible simulation experiment platform.

and driving. In the analysis of allocation strategy, reliability and accuracy are selected as the evaluation indicators for the decision matrix analysis.

To summarize, the analysis of allocation strategy during the navigation process is shown in Table 3.

B. EXPERIMENTAL ENVIRONMENT

The manned submersible simulation experiment platform is shown in Fig. 5.

C. SUBJECTS

Eight subjects (aged from 22 to 25 years, an average of 23 years old, four males and four females) from Northwestern Polytechnic University participated in the experiment. All subjects had a visual acuity of 20/20 or were corrected to normal vision.

D. EXPERIMENTAL PROCESS

The experimental content consisted of 16 experiments combining different strategies, with each experiment lasting approximately 15 minutes. To prevent subjects from memorizing experimental stimulus materials, multiple sets of stimuli were designed and randomly selected for each experiment. Due to the large number of experiments, in order to prevent subjects from being fatigued and resulting in inaccurate experimental data, the experiments were divided into

TABLE 3. Analysis of allocation strategy for the manned submersible in navigation process.

	Function	System function analysis	Decision matrix analysis	Automation level analysis
Assignable	Life support function C1	Information acquisition	Machine	
		Information analysis	Machine	
		Decision selection	Machine	
		Action implementation	Human	Manual adjustment.
			Machine	Automatic adjustment.
	Thruster monitoring function C2	Information acquisition	Machine	
		Information analysis	Machine	The system provides a fault diagnosis result.
			Human-machine	The system provides optional fault diagnosis results.
	Collision avoidance function C3	Information acquisition	Machine	
		Information analysis	Machine	
		Decision selection	Machine	The system provides a decision-making scheme.
			Human-machine	The system provides optional decision-making schemes.
		Action implementation	Human	
	Driving function C4	Action implementation	Human	Manual driving.
			Machine	Automatic driving.
Non-assignable	Communication function (interactive data information) C5	Action implementation	Machine	
	Communication function (voice communication) C5	Action implementation	Human	
	Detection function C6	Information acquisition	Machine	
		Information analysis	Human	
		Decision selection	Human	
	Navigation function C7	Information acquisition	Machine	
		Information analysis	Human	
		Decision selection	Human	

four groups, with each group being carried out at the same time every day. The subjects were asked to rest for 10 minutes after each experiment.

Before the experiment, subjects needed to be briefed on the research purpose, experimental task requirements, simulator functions, and their role in the experiment. After that, they were seated in the manned submersible simulator and adjusted themselves to a more comfortable position, ensuring that they could observe each display screen and operate the oxygen supply panel and general control panel with ease. Next, they conducted several practice experiments on the manned submersible simulation platform to familiarize themselves with both the simulated navigation scene and the SAGAT questionnaire. They were asked to answer task-related questions using the SAGAT questionnaire, which objectively reflected the current level of situation awareness through the accuracy rate of their answers. According to the theoretical model of situation awareness, questions can be categorized into three different levels. To prevent subjects from remembering the questions, 12 questions were randomly selected from the question bank and presented to them. At the same time, it is necessary to control 12 questions covering three levels of situation awareness to ensure the integrity of situation awareness measurement [28].

After conducting practice experiments, formal experiments began. At the end of each formal experiment, subjects were asked to complete the SAGAT questionnaire and the Karolinska Sleepiness Scale (KSS). The videos recorded during the experiments were analyzed using a focus group discussion method. By combining subjects' opinions, tasks were broken down into several subtasks, which were categorized and scored using the VACP scale. For each combination of HFA strategies, a stable process was selected separately from recorded execution process videos as the standard. In this process, subtasks were divided into visible and invisible subtasks based on whether they were observable or not. For visible subtasks, the time information could be directly observed and recorded; for invisible subtasks, the time information was inferred by integrating the subjects' opinions.

E. RESULTS

1) MENTAL WORKLOAD PLAYER

The subtask analysis table of the navigation process is shown in Table 4. The mental workload for combinations of allocation strategies is shown in Table 5. The mental workload diagram for the combination 1,1,1,1 over time is shown in Fig. 6.

2) SITUATION AWARENESS PLAYER

One of the SAGAT questionnaires is shown in Table 6. After excluding abnormal data, seven groups of valid experimental data were obtained, including four groups of males and three groups of females. The situation awareness for combinations of allocation strategies is shown in Table 7.

TABLE 4. Subtask analysis table of navigation process.

Dimension	Subtask description	Rate
Visual	Detect whether alarm information appears	1.0
	Observe the environment ahead	1.0
	Identify operation buttons	3.7
	Identify forward targets	3.7
	Identify images of undersea terrain	3.7
	Check data	4.0
	Read alarm information	5.9
	Read schemes provided by the system	5.9
Auditory	Hear the alarm	1.0
Cognitive	Ensure normal operation of the manned submersible	1.0
	Select buttons or knobs	1.2
	Identify image content	3.7
	Determine whether the data is within a reasonable range	4.6
	Evaluate optional schemes given by the system	6.8
	Plan the route	6.8
Psychomotor	Report to the mother ship	1.0
	Click the collision avoidance direction button	2.2
	Manipulate the handle to drive the manned submersible	4.6
	Adjust the oxygen trigger valve	5.8

TABLE 5. Mental workload for combinations of allocation strategies.

Combinations of allocation strategies (C1, C2, C3, C4)	Mean
1,1,1,1	3.68
1,1,2,1	5.33
1,1,1,3	8.94
1,1,2,3	10.36
1,2,1,1	4.24
1,2,2,1	6.52
1,2,1,3	9.84
1,2,2,3	10.82
3,1,1,1	4.12
3,1,2,1	5.59
3,1,1,3	9.23
3,1,2,3	10.46
3,2,1,1	4.48
3,2,2,1	6.57
3,2,1,3	9.93
3,2,2,3	11.19

3) GAME UTILITY MATRIX

The optimal combination of allocation strategies for mental workload is 1,1,1,1 in Table 5. The impact factor of each assignable function on the mental workload player is:

$$\xi_W = \{\xi_{1W}, \xi_{2W}, \xi_{3W}, \xi_{4W}\} = \{0.124, 0.164, 0.406, 0.036\}.$$

The optimal combination of allocation strategies for situation awareness is 1,1,2,1 in Table 7. Three experts involved in the design of the manned submersible were invited to score. The impact factor of each assignable function on the situation awareness player is:

$$\xi_{SA} = \{\xi_{1SA}, \xi_{2SA}, \xi_{3SA}, \xi_{4SA}\} = \{0.139, 0.139, 0.583, 0.139\}.$$

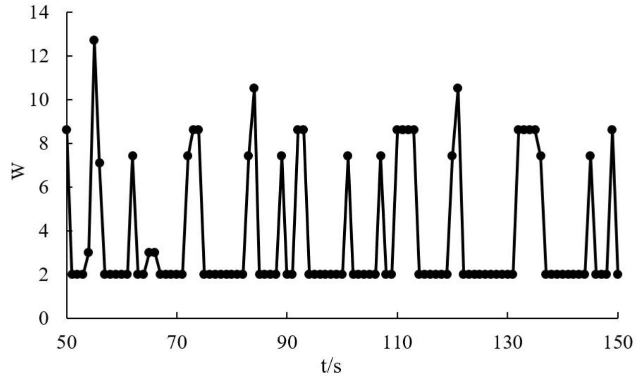

FIGURE 6. Mental workload diagram for the combination 1,1,1,1.

TABLE 6. One of the SAGAT questionnaires.

Serial number	SA level	Question
1	1	What is the value of CO_2 now?
2	1	What direction of the manned submersible is there an obstacle at this moment?
3	1	What is the height of the manned submersible now?
4	1	Did the manned submersible pass by schools of fish during the whole operation?
5	1	What are the alarm messages that used to appear?
6	2	Whether the forward speed is higher or lower than the planned value at this moment?
7	2	Is the thruster speed higher or lower than expected?
8	2	The imaging sonar at this moment shows whether there is a dramatic change in height ahead?
9	3	Which direction may require a collision avoidance operation at the next moment?
10	3	Whether the value of O_2 will be beyond safety at the next moment?
11	3	Whether the direction of travel needs to be adjusted at the next moment?
12	3	Predict the possible future thruster failure.

The set of impact factors of the assignable function ζ_i on two players is:

$$\zeta_1 = (\xi_{1W}, \xi_{1SA}) = (0.124, 0.139);$$
$$\zeta_2 = (\xi_{2W}, \xi_{2SA}) = (0.164, 0.139);$$
$$\zeta_3 = (\xi_{3W}, \xi_{3SA}) = (0.406, 0.583);$$
$$\zeta_4 = (\xi_{4W}, \xi_{4SA}) = (0.036, 0.139).$$

Taking $M = 0.4$, the fuzzy similarity matrix is calculated based on (11)

$$R = \begin{bmatrix} 1 & 0.95676 & 0.29514 & 0.90486 \\ 0.95676 & 1 & 0.33838 & 0.86162 \\ 0.29514 & 0.33838 & 1 & 0.20000 \\ 0.90486 & 0.86162 & 0.20000 & 1 \end{bmatrix},$$

The fuzzy equivalent matrix is obtained by the transitive closure method

$$\hat{R} = \begin{bmatrix} 1 & 0.95676 & 0.33838 & 0.90486 \\ 0.95676 & 1 & 0.33838 & 0.90486 \\ 0.33838 & 0.33838 & 1 & 0.33838 \\ 0.90486 & 0.90486 & 0.33838 & 1 \end{bmatrix}.$$

TABLE 7. Situation awareness for combinations of allocation strategies.

Combinations of allocation strategies (C1, C2, C3, C4)	Mean	SD
1,1,1,1	7.57	0.495
1,1,2,1	10.86	0.639
1,1,1,3	6.43	0.495
1,1,2,3	5.71	0.452
1,2,1,1	10.14	0.350
1,2,2,1	10.29	0.452
1,2,1,3	6.14	0.639
1,2,2,3	5.71	0.452
3,1,1,1	9.29	0.452
3,1,2,1	9.86	0.639
3,1,1,3	6.29	0.452
3,1,2,3	6.00	0.535
3,2,1,1	10.00	0.535
3,2,2,1	8.71	0.452
3,2,1,3	6.29	0.452
3,2,2,3	5.14	0.350

SD: Standard Deviation.

Taking the confidence level $\lambda = 0.6$, the fuzzy clustering matrix is

$$R_\lambda = \begin{bmatrix} 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 \end{bmatrix}.$$

Therefore, the four assignable functions can be grouped into two categories: one category includes the life support function, thruster monitoring function, and driving function; the other category includes the collision avoidance function. The clustering of impact factors is analyzed to obtain the strategy set of the mental workload player $S_1 = (C_1, C_2, C_4)$, which contains eight strategies, and the strategy set of the situation awareness player $S_2 = (C_3)$, which contains two strategies.

The utility values are standardized as shown in (14)

$$\begin{aligned} u_1(W) &= \frac{W_{nmz} - W_{\min}}{W_{\max} - W_{\min}} \\ u_2(SA) &= \frac{SA_{\max} - SA_{nmz}}{SA_{\max} - SA_{\min}} 1 \le n \le 8, 1 \le m \le 2, z = 1 \end{aligned} \tag{14}$$

where W_{nmz} and SA_{nmz} are respectively the utility value of the mental workload and the utility value of the situation awareness when assignable functions belonging to the mental workload player P_1 adopt strategy n, assignable functions belonging to the situation awareness player P_2 adopt strategy m, and non-assignable functions adopt a fixed strategy z. The non-cooperative game utility matrix for mental workload and situation awareness of different combinations of allocation strategies during the navigation process is shown in Table 8.

4) NASH EQUILIBRIUM STRATEGY

Regardless of the initial strategy chosen, the Nash equilibrium strategy for both players $S = \{(S_1), (S_2)\} = \{(C_1, C_2, C_4), (C_3)\} = \{(1, 1, 1), (2)\}$ can be found within two game rounds. Any three game iterative processes are presented in Fig. 7.

TABLE 8. Mental workload - situation awareness utility matrix during navigation process.

Mental workload P_1 (C1, C2, C4)	Situation awareness P_2 (C3): 1	Situation awareness P_2 (C3): 2
1, 1, 1	0.000, 0.575	0.220, 0.000
1, 1, 3	0.700, 0.774	0.889, 0.900
1, 2, 1	0.075, 0.126	0.378, 0.100
1, 2, 3	0.820, 0.825	0.951, 0.900
3, 1, 1	0.059, 0.274	0.254, 0.175
3, 1, 3	0.739, 0.799	0.903, 0.850
3, 2, 1	0.107, 0.150	0.385, 0.376
3, 2, 3	0.832, 0.799	1.000, 1.000

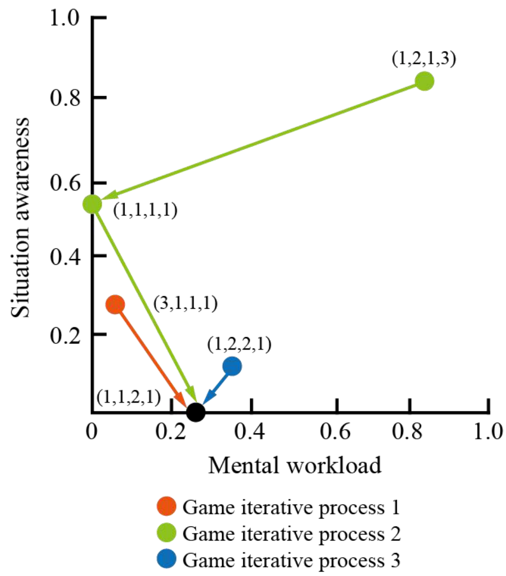

FIGURE 7. Non-cooperative game iterative processes of mental workload and situation awareness.

The changes in mental workload utility and situation awareness utility for different combinations of HFA strategies are shown in Fig. 8 and Fig. 9, respectively.

5) COMPARISON OF OPTIMIZATION METHODS

The TOPSIS and grey correlation degree methods are commonly used for solving multi-objective problems, so they were chosen to compare with non-cooperative game method. Taking the mental workload weight $\omega_1 = 0.5$ and the situation awareness weight $\omega_2 = 0.5$, the optimal strategy obtained by the TOPSIS method is $S = \{(S_1), (S_2)\} = \{(C_1, C_2, C_4), (C_3)\} = \{(1, 2, 1), (1)\}$. The equations of the TOPSIS method are shown in (15) and (16).

$$\begin{cases} d_i^+ = \sqrt{\sum_{j=1}^{2} \left(v_{ij} - v_j^+\right)^2} \\ d_i^- = \sqrt{\sum_{j=1}^{2} \left(v_{ij} - v_j^-\right)^2} \end{cases} \tag{15}$$

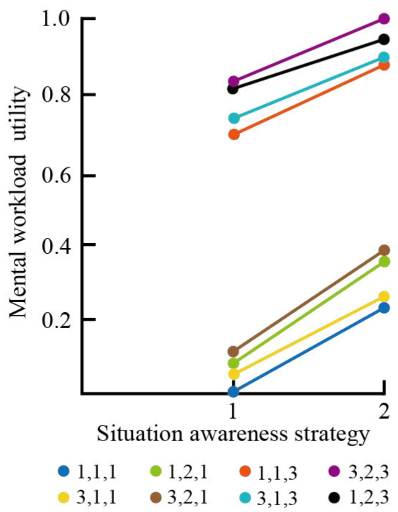

FIGURE 8. The changes in mental workload utility for different combinations of HFA strategies.

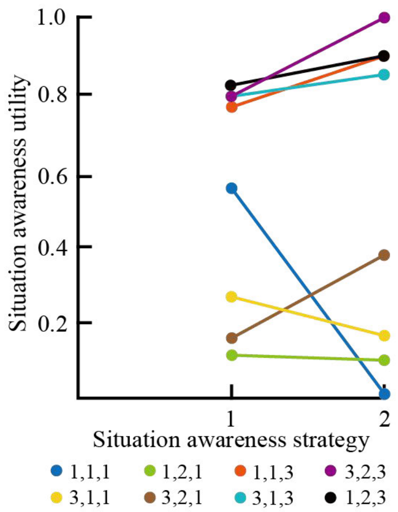

FIGURE 9. The changes in situation awareness utility for different combinations of HFA strategies.

where the values of mental workload and situation awareness normalized by equation (14) are noted as u_{i1} and u_{i2}, so $v_{ij} = \omega_j \times u_{ij}$, $v_j^+ = \min v_{ij}$, and $v_j^- = \max v_{ij}$.

$$T_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{16}$$

where the optimal strategy is the one that corresponds to the maximum value of T_i.

The optimal strategy obtained by the grey correlation degree method is $S = \{(S_1), (S_2)\} = \{(C_1, C_2, C_4), (C_3)\} = \{(1, 2, 1), (1)\}$. The equations of the grey correlation degree method are shown in (17), (18), (19), and (20).

$$\tau_{ij} = \frac{\Delta \min + \rho \Delta \max}{\left| u_{ij} - u_j^+ \right| + \rho \Delta \max} \tag{17}$$

$$\gamma_j = \frac{1}{n} \sum_{i=1}^{n} \tau_{ij} \tag{18}$$

TABLE 9. Calculation results of the TOPSIS method and the grey correlation degree method.

Strategy combinations (C1, C2, C3, C4)	TOPSIS	Grey correlation degree
1, 1, 1, 1	0.654	0.283
1, 1, 1, 3	0.264	0.737
1, 2, 1, 1	0.897	0.100
1, 2, 1, 3	0.177	0.823
3, 1, 1, 1	0.809	0.165
3, 1, 1, 3	0.232	0.769
3, 2, 1, 1	0.870	0.128
3, 2, 1, 3	0.185	0.816
1, 1, 2, 1	0.852	0.112
1, 1, 2, 3	0.105	0.895
1, 2, 2, 1	0.737	0.241
1, 2, 2, 3	0.078	0.926
3, 1, 2, 1	0.783	0.215
3, 1, 2, 3	0.126	0.877
3, 2, 2, 1	0.620	0.380
3, 2, 2, 3	0.000	1.000

TABLE 10. Comparison of the optimal solutions of three optimization methods.

Optimization method	Mental workload	Situation awareness	Alertness Mean	Alertness SD
Non-cooperative game	5.33	10.86	2.38	0.48
Grey correlation degree	4.24	10.14	3.00	0.50
TOPSIS	4.24	10.14	3.00	0.50

SD: Standard Deviation.

$$\omega_j = \frac{\gamma_j}{\sum_{j=1}^{2} \gamma_j} \tag{19}$$

$$P_i = \sum_{j=1}^{2} \omega_j u_{ij} \tag{20}$$

where $u_j^+ = \min u_{ij}$, $\Delta \min = \min \left| u_{ij} - u_j^+ \right|$, and $\Delta \max = \max \left| u_{ij} - u_j^+ \right|$. ρ is the resolution coefficient, which generally lies between [0, 1] and is often taken as 0.5.

Calculation results of the TOPSIS method and the grey correlation degree method are shown in Table 9.

The optimal HFA strategies for three optimization methods are shown in Fig. 10.

Both mental workload and situation awareness are highly correlated with alertness, so alertness is chosen as the combined benefit of mental workload and situation awareness for comparing solutions [29], [30], [31]. The KSS is used to assess levels of alertness. Comparison of the optimal solutions of three optimization methods is shown in Table 10.

VI. ANALYSIS AND DISCUSSION

A. NASH EQUILIBRIUM STRATEGY

During the operation of the manned submersible, oceanauts need to complete more complex cognitive activities for a long time, which can lead to fatigue and reduce human reliability.

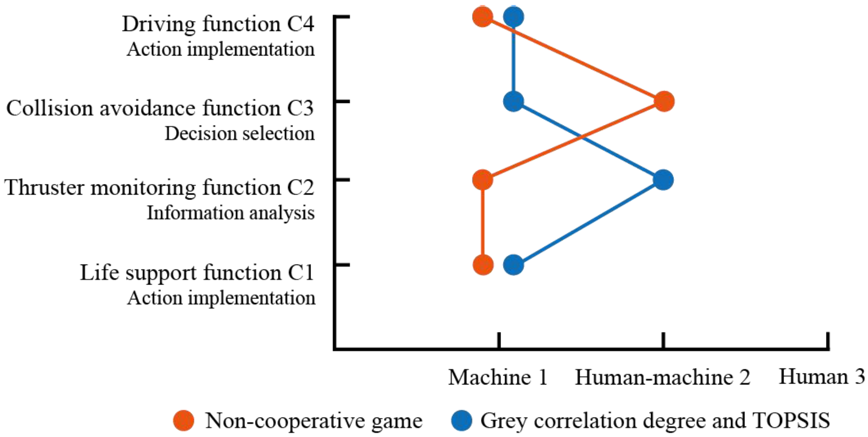

FIGURE 10. **The optimal HFA strategies for three optimization methods.**

The paper selects mental workload and situation awareness as the optimization objectives from the perspective of HFA, and adopts the non-cooperative game method to derive the optimal combination of HFA strategies for the navigation process. It can be concluded that there is no absolute optimal strategy that can optimize both mental workload and situation awareness during the navigation process from Table 8, so further analysis and discussion of each strategy are necessary.

Compared with other strategies of player P_1 from Fig. 8, $S_1 = \{(C_1, C_2, C_4)\} = \{(1, 1, 1)\}$ has a strict advantage in mental workload utility, which satisfies (13). At this time, any strategy change made by P_1 will reduce its own benefits. As shown in Fig. 9, the strategy $S_2 = (C_3) = (2)$ is the optimal solution of P_2 under the optimal strategy of P_1. Therefore, P_1 cannot unilaterally make strategy changes in order to protect its own benefits. The game is reached Nash equilibrium. The non-cooperative game method can achieve a balance between mental workload and situation awareness to enhance human reliability. Balancing the mental workload and situation awareness can help improve inattention and reduce fatigue [32], [33], [34], [35].

B. COMPARISON OF OPTIMIZATION METHODS

As shown in Fig. 10, two solutions are consistent with the literature [36], [37], which suggested that action implementation and information acquisition were assigned to higher levels of automation, while information analysis or decision selection was assigned to lower levels of automation, helping to obtain higher situation awareness.

As shown in Table 10, the non-cooperative game method is significantly better than the TOPSIS method and the grey correlation degree method in terms of situation awareness and alertness. Compared with the TOPSIS method, the non-cooperative game method improves the shortcomings of subjective weights. The optimal solution of the TOPSIS method will change depending on weights of optimization objectives, and subjective weights reduce the credibility and universality of the optimal solution. Compared with the grey correlation degree method, the non-cooperative game method improves the disadvantages of complex data processing and the subjective resolution coefficient. The calculation of correlation degrees becomes more tedious when dealing with a large amount of data. And the subjective resolution coefficient reduces the credibility of the optimal solution. The non-cooperative game method analyzes and solves problems from an objective perspective, guiding players to compete and cooperate during the gaming process. It can simultaneously optimize multiple objectives to reach the equilibrium state, which enhances the stability of the optimal solution. The Nash equilibrium point can be found with just a few rounds of comparison, and the solution speed is fast.

VII. CONCLUSION

The non-cooperative game model is used to solve the optimization problem of HFA for the manned submersible. The effectiveness and practicality of the proposed method are proven by using the navigation process as an example. The non-cooperative game method improves the subjectivity and low stability of the TOPSIS method and the grey correlation degree method, providing a feasible solution for discrete multi-objective optimization problems in the field of function allocation and laying the foundation for dynamic HFA.

In fact, there are more factors that affect the HFA during the operation of the manned submersible, so more objectives need to be optimized in the actual function allocation. Furthermore, compared to static function allocation, dynamic function allocation is more beneficial for humans in maintaining situation awareness and manual skills. Therefore, establishing a multi-objective game optimization model and constructing an effective and applicable trigger mechanism are the focus of the next research.

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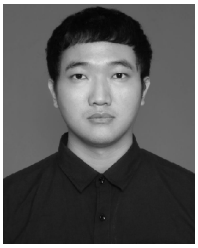

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