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An Intelligent Decision Algorithm for the Generation of Maritime Search and Rescue Emergency Response Plans

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ABSTRACT Maritime search and rescue (SAR) decisions are the most important part of maritime SAR operations. In the process of making maritime SAR decisions, a key factor affecting efficiency and success rate is how to quickly respond to accidents and develop an emergency response plan. At present, maritime SAR emergency response plans are still mostly obtained through a combination of drift prediction models and SAR experience. There is a lack of SAR resource scheduling and SAR task assignment. The primary purpose of this paper is to explore the possibility of using an intelligent decision-making algorithm to formulate maritime SAR emergency response plans so as to produce results more scientifically. First, the relevant research areas and research data are briefly introduced, and the main mathematical models involved in the optimal search theory are expounded. Next, key technologies involved in the process of maritime SAR emergency response plan generation, including the determination of search area, the scheduling of SAR resources, the allocation of search tasks, and the planning of search routes, are analyzed in detail. Two optimization model algorithms, namely the SAR resource scheduling model based on genetic simulated annealing algorithm (GSAA) and the regional task allocation algorithm based on space-time characteristics, are proposed as approaches to solving the problem of resource scheduling and task allocation. Finally, the effectiveness and optimization of the proposed algorithms are verified by analyzing the emergency response of a real case which occurred in the Bohai Sea and comparing the different schemes. Through the algorithm proposed in this paper, the efficiency of maritime SAR operations can be effectively improved and the loss of life and property can be reduced.

INDEX TERMS Maritime SAR, resources scheduling, GSAA, space-time characteristics, task allocation, optimization.

I. INTRODUCTION

Because of advances in technology, maritime SAR capabilities and technical levels have improved significantly. However, many problems still plague the maritime SAR process, such as imperfect emergency systems, untimely emergency response, and unreasonable plans. The damage caused by a marine accident is immeasurable. When the ships "TIANYU 2" and "LIAOSUIYU 66528" collided in September 2017, 6 people died due to the inability to formulate a scientific SAR plan in time [1]. Therefore, further research into maritime SAR decision-making algorithms is urgently needed in order to improve maritime SAR capabilities.

At present, domestic and foreign scholars have done a lot of research on the issue of SAR decision-making. For determining the search area, Zhang Jinfeng et al. proposed a probabilistic model for predicting the object's drift velocity and position in a sequential manner [2]; Huang Juan and Liu Tongmu et al. used the Lagrangian tracking

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algorithm and the Runge-Kutta method to study the drift trajectory of the drowning personnel [3], [4]. Wang Boyan and Xiao Fangbing et al. simulated and analyzed the drift prediction process by Monte Carlo algorithm and calculated the search area [5], [6]. Considering the scheduling problem of resources, Koczkodaj W and Orlows M studied the emergency resource scheduling problem in drift target search and rescue (SAR) [7]; Gilbert Laporte introduced the concept of rescue resource packages in consideration of the marine environment and established a multi-level emergency material dispatch optimization model for marine emergency events [8]. In terms of ship scheduling, Linet Özdamar et al. constructed a ship ranking model for emergency ship design [9]; Hu Qihua et al. studied the optimization of maritime SAR forces based on genetic algorithms (GA) [10]. About the allocation of search tasks, B.O. Koopman first proposed the optimal search theory, which has a profound impact on guiding maritime SAR operations [11]. Thomas M Kratzke and L.D. Stone et al. applied the theory of optimal search to maritime SAR and assigned search tasks according to the probability of success [12], [13]. Xiao Fangbing studied the key technologies in maritime SAR decision-making [14] and Xing Shengwei studied the global optimization model of joint aeronautical and maritime search and proposed a SAR task assignment algorithm based on overall splitting [15].However, many challenges in the SAR decision-making process persist. (1) Complex sea environments make target drift prediction and search area delineation inaccurate. Although particle tracking algorithms such as Lagrange, Longgutta, and Euler have been widely used to solve this problem, the impact of SAR target types on drift prediction is rarely considered. (2) SAR resource scheduling is limited to single SAR units and resource scheduling plans are mostly based on qualitative rather than quantitative research; At present, most scholars generally use GA for SAR resource scheduling, but the optimization goals are mostly time and cost, not combined with the optimal search theory, and GA is easy to fall into precocity. (3) Since the task allocation of the SAR unit mostly utilizes the optimal search rectangle allocation algorithm based on optimal search theory, the resulting task areas often overlap and cannot cover the entire search area, resulting in a possibility of missing the target. The global optimization model proposed by Xing Shengwei cannot take into account the priority of the task, although the overall search area can be divided.

In consideration of the problems listed above, this paper provides the following solutions. (1) In the process of determining the search area, the running time of the prediction model with the number of particles at 200, 500, 800, and 1000 is calculated under different prediction durations to obtain the appropriate number of scatter points. Through comparative analysis, it is found that when the number of particles is 500, the model runs for a short time and the variation with the predicted duration is the smallest. Therefore, 500 random points are randomly generated according to the Monte Carlo algorithm as possible locations for the SAR target in order to reflect the continuity and randomness of the drift prediction process. Then, the Lagrange particle tracking algorithm is used to predict the drift of the 500 particle points because of the accuracy of the Lagrangian method in tracking a finite number of particles. Finally, the Graham scan algorithm [16] and the minimum area bounding rectangle (MABR) generation algorithm are used to calculate the drift range of the 500 particles, and the search region is determined according to the drift time. (2) In order to optimize the SAR resource scheduling scheme, this paper establishes a SAR resource scheduling model based on genetic simulated annealing algorithm (GSAA) with the goal of maximizing the probability of successful search and rescue (POSSAR) and taking the total ship demand and search time as constraints. We regard POSSAR as the product of probability of search success (POS) and probability of rescue (POR), fully considering the rescue conditions of the SAR unit, and making the resource allocation plan more reasonable. In addition, this paper uses GSAA to solve the model, which largely avoids the situation in which the model falls into a local optimal solution. (3) For the task assignment problem, this paper designs a new regional task allocation algorithm based on space-time characteristics. The algorithm introduces the overall splitting principle based on the theory of optimal search, which not only enables the region with higher POS to be searched preferentially, but also covers the entire search area, without any overlap between the task regions. This will not only improve SAR efficiency, but also reduce the probability of missing targets and avoid invalid searches (secondary search for overlapping areas of tasks).

The contents of each section are briefly described as follows: Section 2 mainly describes the relevant situation in the study area. Section 3 illustrates the data used in the study. Section 4 mainly analyzes the drift prediction model and the method of determining the convex hull and MABR. Section 5 mainly demonstrates the mathematical model involved in the maritime optimal search theory. Section 6 introduces the resource scheduling model and the GSAA algorithm for solving the scheduling problem. Section 7 introduces the relevant principles and steps of the regional task allocation algorithm. Section 8 describes the decision-making and response results of a real case occurring in the Bohai Sea. In section 9, the effectiveness and optimization of the proposed algorithm are verified by comparing different response schemes. Section 10 summarizes the paper.

II. RESEARCH AREA

In recent years, with the rapid development of China's shipping industry, ports and waterways have become increasingly crowded, resulting in substantial maritime traffic accidents. From January 2018 to June 2019, there were 2,556 dangerous accidents that occurred in China's sea area, with 19,111 people and 2,174 ships in distress. The distribution of China's marine accidents since 2018 is shown in Fig. 1.

This paper regards the Chinese sea area as the research area mainly for the following two reasons. First, the Chinese sea

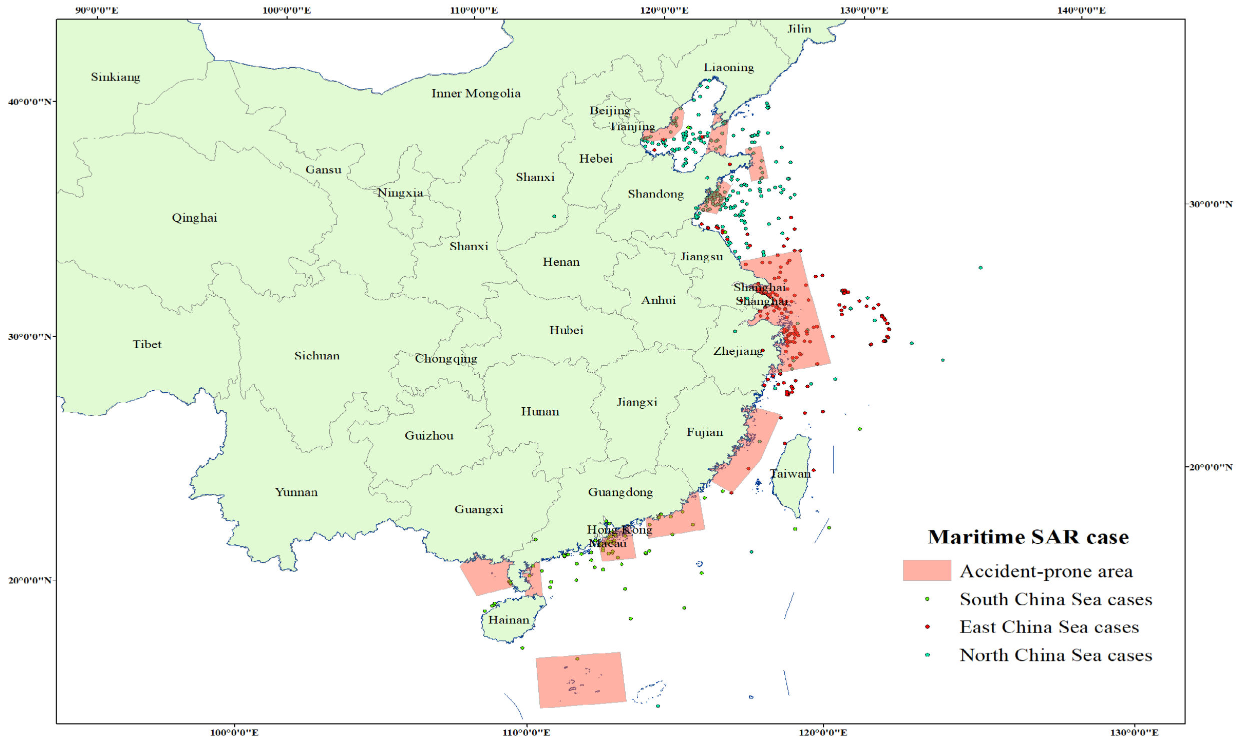


FIGURE 1. Distribution of maritime accidents and accident-prone areas in China since 2018.

area has complex wind and wave conditions, and is prone to bad weather, such as fog. Second, sea accidents in China's sea areas occur frequently, and the types of accidents are diverse.

III. RESEARCH DATA

A. MARINE DYNAMIC ENVIRONMENT DATA

Marine dynamic environment data mainly includes wind, wave, current, and sea temperature data, which play a vital role in maritime SAR decisions. Wind field data is acquired from the European Centre for Medium-Range Weather Forecasts (ECMWF), wave field data is from the Global Forecast System (GFS), and the flow field and sea temperature data are from the National Marine Environmental Forecasting Center. The data collection process is as follows: the data is requested according to the range; then the obtained NC (NetCDF, Network Common Data Form) file is preprocessed; and finally the data in GeoJSON and PNG format is used for analysis and display. In this paper, wind and flow data are used to predict the drift trajectory of the target, while the sea temperature data is used to estimate the survival time of the SAR target. Visualizations of various data are shown in Fig. 2. In Fig. 2a, the color of the wind symbol corresponds to the wind legend, the color and number in the base map correspond to the temperature legend. The wave legend in Fig. 2b represents the wave which is indicated by the base color.

B. AUTOMATIC IDENTIFICATION SYSTEM (AIS) DATA

AIS data refers to the ship's real-time location and information data obtained through the automatic identification system [17], [18]. AIS data is mainly obtained by calling the free shore-based AIS and radar AIS interface. This paper uses AIS data for the allocation of SAR resources, and assigns SAR missions to selected SAR resources through AIS information. The visualization of AIS data is shown in Fig. 3.

IV. DETERMINATION OF THE SEARCH AREA

A. DRIFT PREDICTION MODEL

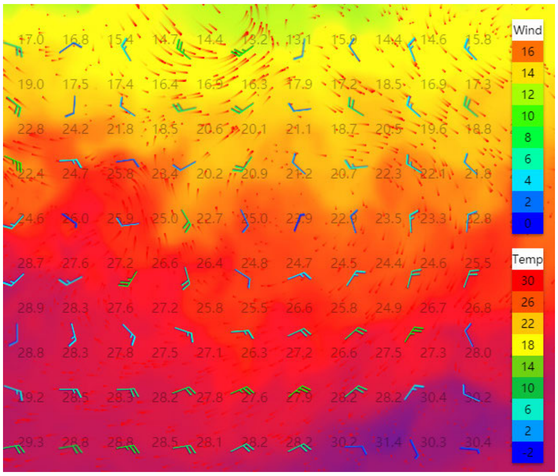
Knowing the location of a ship or life accurately is a prerequisite for conducting SAR operations. After the accident, the ship in distress will be affected by the surrounding marine environment and drift. Therefore, accurately predicting the ship's drift trajectory is the key to successful SAR work. In this paper, the Lagrange particle tracking algorithm is used to predict the drift trajectory of SAR targets.

Firstly, the force analysis of the distress target at sea is carried out. The force formula for the distress target is:

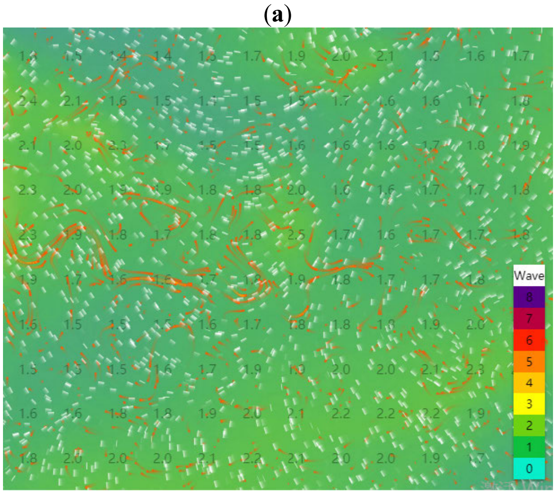
$$\mathrm{M} \times \frac{d_v}{d_t} + mf = F_w + F_c \tag{1}$$

where M refers to the mass of the distress target; d_v refers to the speed of the distress target; mf is the Coriolis force, referring to the influence of the earth's rotation on the fluid. F_w refers to the force of the wind on the portion of the distressed target exposed above the surface of the sea, and F_c is the force which seawater exerts on the distress target.

The Lagrange particle tracking algorithm [19] is then used to determine the displacement of the particles. Through the



(a)



(b)

FIGURE 2. **(a) Sea temperature (°C) and wind (m/s) field visualization, (b) Wave (m) and flow (m/s) field visualization.**

algorithm, the variation of the physical quantity of the particle during the movement can be recorded, and the motion trajectory of the particle can be obtained intuitively. When the number of particles is small, the Lagrangean method has higher tracking accuracy, and the calculation amount is less than that of the high-order Euler method [20] and Runge-Kutta method. The calculation is as follows:

$$\frac{dX}{dt} = A\left(X_t\right) + B(X, t)Z_n \tag{2}$$

where A represents the drift coefficient, X_t is the displacement of the particle, B is the diffusion coefficient, and Z_n represents an independent random number [21].

The position of the particles is determined by solving the displacement of the particles at each moment, and the dynamic tracking of the particles is realized. In the solution of the drift prediction equation, some coefficients are obtained empirically and experimentally. Therefore, the calculation result of the predicted trajectory will inevitably produce errors. In order to improve the accuracy of the drift prediction results, the drift trajectory of five hundred particles is calculated in the model, and the SAR range is determined by the drift range of those particles. The drift trajectory is shown in Fig. 4.

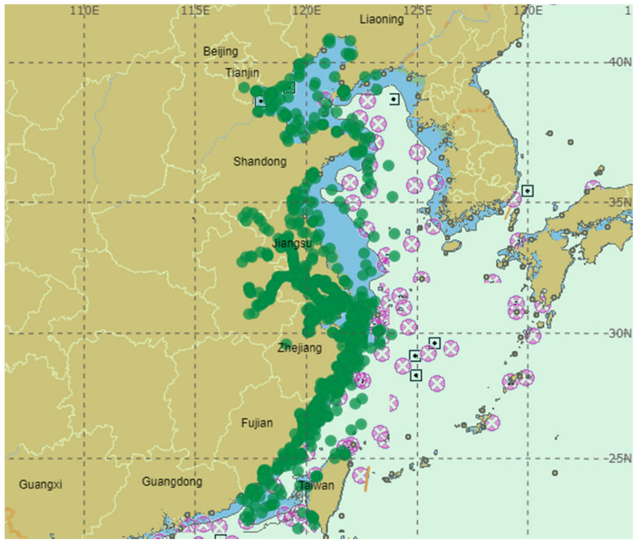


FIGURE 3. **The visualization of AIS data, where green dots represent ships acquired at the current moment.**

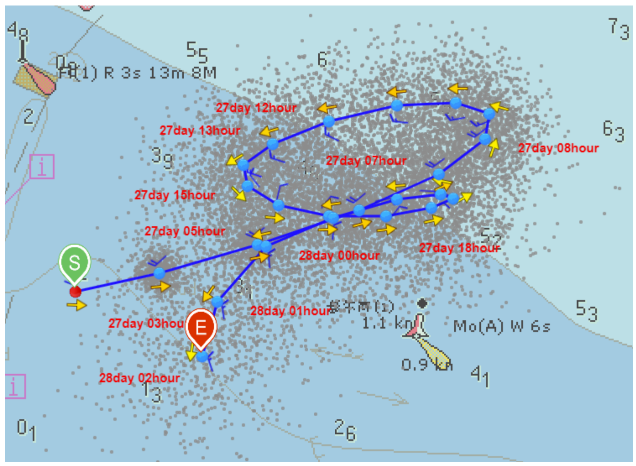


FIGURE 4. **The drift trajectory of the SAR target and the predicted scatter distribution at each moment.**

B. CONVEX HULL GENERATION

In this paper, the Graham scanning algorithm is used to generate a convex hull [22]. Graham's scan is a method of finding the convex hull of a finite set of points in the plane with time complexity O (n log n). Firstly, add two points, A and C, then insert the third point D and calculate the cross product of AC × CD. If the cross product is less than 0, it means that the ∠ACD in the counterclockwise direction is greater than 180 degrees, so delete C and join point D; then follow this step to join point E. With E as the starting point, you can find two convex polygons which are ADE and EFGA above the AD. The convex hull is obtained by merging two convex polygons. The result is shown in Fig. 5.

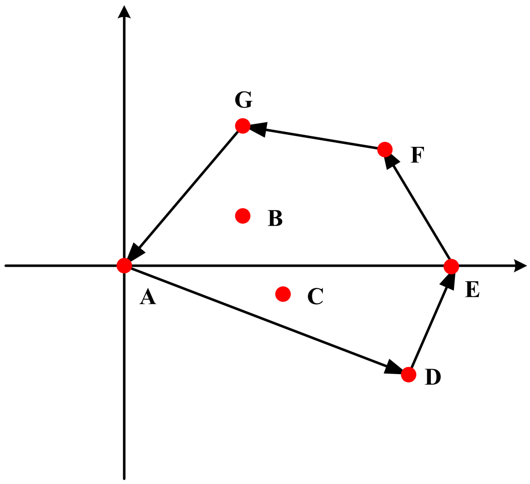


FIGURE 5. Schematic diagram of convex hull generation method.

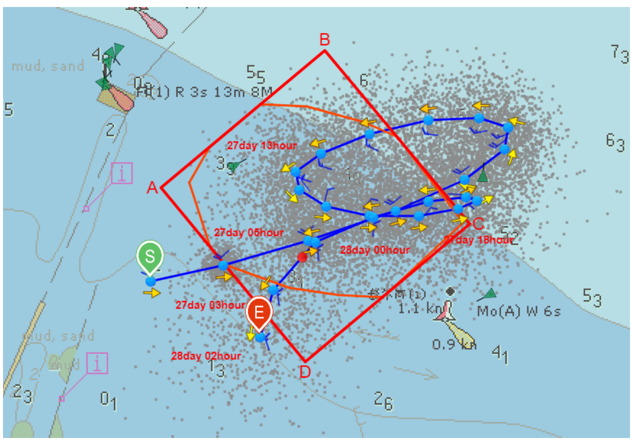


FIGURE 6. Visualization of rectangular search area after normalization of convex hull.

C. MABR GENERATION

If the convex polygon is used as the search area, it will affect search route planning. Therefore, the convex polygon needs to be adjusted to generate the MABR containing the convex polygon. The steps of the algorithm are as follows:

- Take any edge of the convex hull as an edge of the rectangle and establish a coordinate system with the edge as the X axis.
- Find the point A with the largest X coordinate, the point B with the smallest X coordinate, and the point C with the largest Y coordinate in the coordinate system. Construct two lines perpendicular to the X-axis, one through A and one through B. Construct a third line parallel to the X-axis through C. These three lines and the X-axis itself form the boundary rectangle.
- Calculate the area of the acquired rectangle and save the area and boundary data.
- Repeat the above steps to determine and save the rectangular parameter with the smallest area as the MABR.

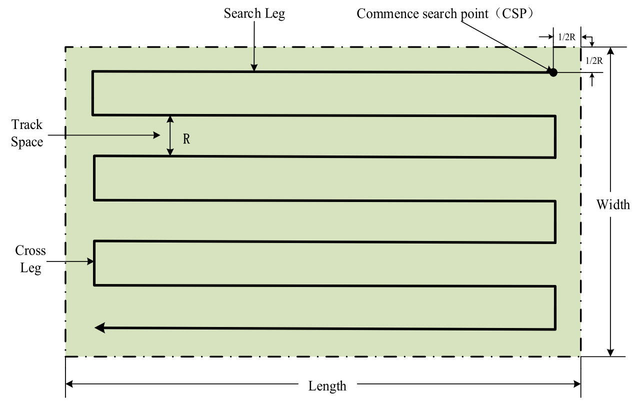


FIGURE 7. Parallel line search method.

- Finally, the MABR is used as the initial search area (as shown in Fig. 6), and the search task is allocated.

V. MATHEMATICAL MODEL IN SEARCH THEORY

A. PROBABILITY OF CONTAINMENT

The probability of containment (POC) refers to the probability that the SAR target exists in a certain area, which is an important factor affecting the POS [23]. This article considers the POC as consisting of two parts. One is the scatter probability, or the ratio of the particle numbers in a region to the particle numbers in the whole region. The other is the distance probability, or the superposition of the inverse distance weights [24] for a region containing cells. The specific calculation formula is as follows:

$$POC = num/Num + \sum_{i=1}^{n} \frac{\frac{1}{d_i}}{\sum_{i=1}^{N} \frac{1}{d_i}} \tag{3}$$

where *num* is the number of particles included in the region; *Num* is the total number of particles included in the entire search area; n is the number of cells in the region; N is the total number of cells; d_i is the distance from cell i to the selected drift time point.

B. PROBABILITY OF DETECTION

The probability of detection (POD) refers to the probability that a SAR target can be found in a given search area, and it is an important indicator for measuring the search effect of the search unit in the search area [25]. As the search area expands, the distance between the SAR target and the SAR unit will also increase, and the POD will decrease. The probability of discovery is mainly affected by three factors: the size of the search area (A), the sweep width of the detection equipment (W), and the effective path length of the SAR unit in the search area (L). This paper assumes that the ship selects the parallel line search method with less turning times and high search efficiency during the search process (as shown in Fig. 7), so the POD is related to the sweep width and the route spacing.

Sweep width refers to the effective distance that the detector can find the SAR target in a specific search environment,

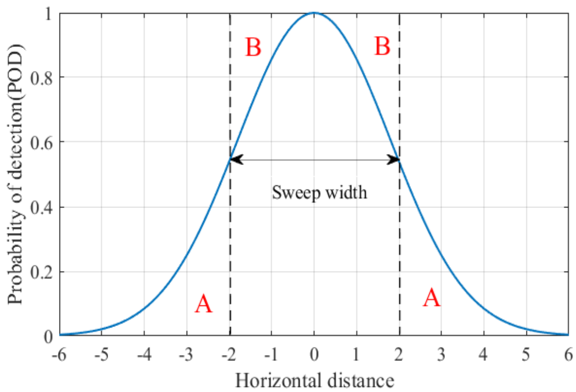


FIGURE 8. Determine the sweep width by lateral distance curve.

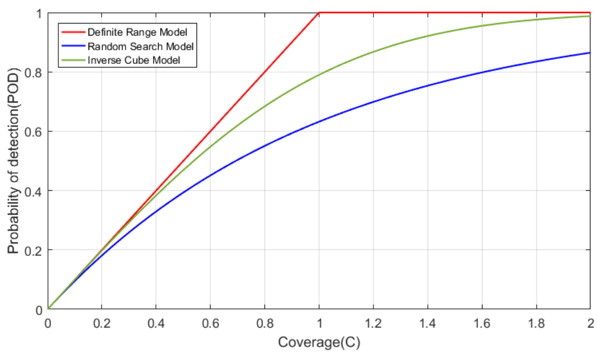


FIGURE 9. Comparison of three different detection function curves.

which is a measure of the ship's search ability. It is often necessary to perform a statistical analysis of a large amount of experimental data and actual case data to determine its value. Geometrically, the sweep width satisfies the horizontal function (as shown in Fig. 8). Different detectors have different horizontal distance curves in different search environments for different SAR targets. Usually, the lateral curve of the detector can be drawn by analyzing a large amount of experimental data [26].

As can be seen from Fig. 8, the POD is the largest when the lateral distance is 0. As the lateral distance increases, the POD gradually decreases, eventually reaching zero. When the lateral distance is such that the area above the curve (B) is equal to the area under the curve (A), the value is the sweep width of the detector in a given environment.

The coverage (C) can be calculated by the sweep width (W) and the track spacing (R). The calculation formula is as follows:

$$C = \frac{W \times L}{A} = \frac{W}{R} \tag{4}$$

where L is the effective path length; A is the size of the search area.

Studies have shown that there is a clear functional relationship between POD and coverage [27]. In Fig. 9, three detection models are introduced for the relationship between POD and coverage representing the definite range model (see formula 5), the random search model (see formula 6) and the inverse cube model (see formula 7) [28], [29]. The calculation formula is as follows:

$$POD = \frac{W \times L}{A} \tag{5}$$

$$POD = 1 - exp(-\frac{W \times L}{A}) \tag{6}$$

$$POD = erf\left(\frac{\sqrt{\pi}}{2}\frac{WL}{A}\right) \tag{7}$$

where erf is the error function.

As can be seen from Fig. 9, for the definite range model, the POD gradually increases and the growth rate (slope) does not change as the coverage rate increases. When the coverage rate is 1, the POD reaches the upper limit. For the inverse cube model and the random search model, the growth rate (slope) of the POD is gradually reduced as the coverage increases. This is because the probability of overlapping search becomes larger as the search activity progresses, which in turn reduces the growth rate of the POD. Therefore, the latter two models are closer to the reality of actual searches. In the search process, the SAR targets show the characteristics of random motion because of the complexity of the maritime SAR environment. The inverse cube model is an estimate of the search detection rate under ideal detection conditions, which does not reflect the random motion characteristics of the SAR targets well. The random search model is an estimate of the search detection rate in a complex maritime SAR environment, which can better reflect the actual movement of the SAR target. Therefore, this paper uses the random search model. The model formula is as follows:

$$POD = 1 - exp(-C) \tag{8}$$

where C is the coverage.

C. PROBABILITY OF SEARCH SUCCESS

Probability of search success (POS) is the main indicator for measuring SAR operations [30]. The size of the POS directly affects the SAR resource scheduling scheme and the SAR mission allocation scheme. The POS is related to the POC and POD [31]. The calculation formula is as follows:

$$POS = POC \times POD \tag{9}$$

VI. SAR RESOURCE SCHEDULING

Modeling and solving the SAR resource scheduling problem is a critical element in informing the disposition of SAR resources. In order to make the model more optimized and close to the actual SAR operations, the following assumptions are made:

- There are enough SAR resources around the search area.
- Relevant information and performance parameters of SAR resources can be obtained through AIS information.
- After determining the search area, the probability that the SAR target exists in the search area is 100%.

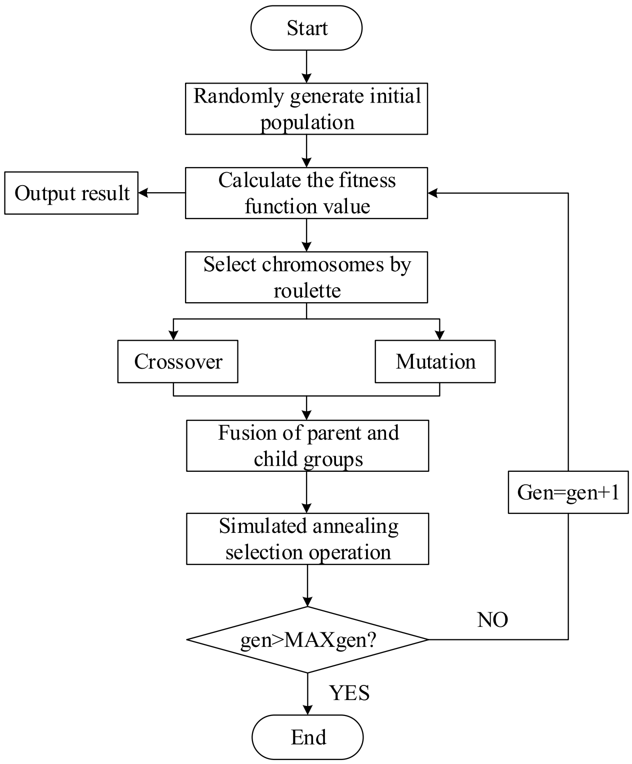


FIGURE 10. **Flow chart of genetic simulated annealing algorithm.**

- We regard the POC value as 1.
- The SAR unit performs an overlay search on the search area and the search areas of the SAR units do not overlap with each other.
- The type of SAR resource is not considered.

A. INTRODUCTION OF GSAA

The GSAA is an optimization algorithm combining GA and simulated annealing algorithm (SA) [32]. GA is a random search algorithm that simulates the evolution of biological processes. Its advantage is that it has inherent hidden parallelism and good global search ability. Unfortunately, it also suffers from weak local search ability and tends to result in premature convergence [33]. The idea of SA takes its inspiration from the metallurgical process of solid annealing. It revolves around repeatedly choosing between the last-chosen solution and a randomly selected similar solution using a probability distribution which favors the better of the two solutions more and more strongly as time goes on. Its advantage is that it has strong local search ability and is capable of randomly "jumping out" of a locally optimal solution. The disadvantage is that the search speed is slow and the execution time is long [34], [35]. Fortunately, the two methods can be combined so as to make up for each other's shortcomings and deficiencies. This ensures good search efficiency and avoids falling into locally optimal solutions, thus establishing a better optimization algorithm [36]. The specific process of the GSAA is shown in Fig. 10.

B. FUNCTION ANALYSIS

Different SAR resources have different equipment and performance, so a specific objective function is needed to measure the strengths and weaknesses of different SAR resources [37]. This paper uses the maximization of POSSAR as the objective function to conduct SAR resource combination evaluation. The POSSAR is affected by two factors: POS and POR. The specific calculation formula is as follows:

$$f(x) = max(POSSAR) \tag{10}$$

$$POSSAR = POS \times POR = POD_s \times POR \tag{11}$$

where POD_s is the POD of entire search area.

1) POD OF THE ENTIRE SEARCH AREA

In the resource scheduling process, we need to consider the POD of the entire search area [38]. Before that, though, we first need to calculate the coverage of the search area. When the coverage of the entire search area is calculated, the total coverage becomes a superposition of the coverage for each SAR unit. The specific calculation formula is as follows:

$$C = \frac{\sum_{i=1}^{k} L_i \times W_i}{S} (k \leq n) \tag{12}$$

$$L_i = \frac{S_i}{R} \tag{13}$$

$$S_i = (T - t_i) \times W_i \times V_{Si} \tag{14}$$

$$t_i = d_i / v_i \tag{15}$$

$$T = \frac{S + \sum_{i=1}^{k} t_i \times W_i \times V_{Si}}{\sum_{i=1}^{k} W_i \times V_{Si}} (k \leq n) \tag{16}$$

where S_i is the search area of the i^{th} SAR unit; S is the total area; L_i is the effective path length of the i^{th} SAR unit; W_i is the sweep width of the i^{th} SAR unit; T is the total time taken to perform the search task; t_i is the time taken by the i^{th} SAR unit to reach the search area; d_i is the distance from the i^{th} SAR unit to the search area; v_i is the maximum safe speed of the i^{th} SAR unit in the current sea state; V_{Si} is the search speed of the i^{th} unit; k is the number of SAR units selected; n is the number of all available SAR units in the vicinity.

According to formula (8), we can find the value of POD_s.

2) PROBABILITY OF RESCUE SUCCESS

The probability of rescue success (POR) refers to the probability that the drowning person can be salvaged and rescued after being discovered. It is an important indicator for measuring the effectiveness of a rescue operation from the perspective of personnel in danger of drowning. The probability of rescue success is mainly related to the medical level of the SAR unit and the medical needs of the drowning personnel. The relationship between the three can be expressed as:

$$POR = \frac{\sum_{i=1}^{k} ML_i / ML_r}{k} \tag{17}$$

where ML_i is the medical level of each SAR unit; ML_r is the medical demand of the SAR target; k is the number of selected SAR units.

TABLE 1. Reference time of human body in different sea temperatures.

Sea temperature	Estimated survival time
<0°C	0.08h
1°C	0.13h
2°C	0.25h
2.5°C	0.5h
5°C	1h
10°C	3h
15°C	6h
20°C	12h
25°C	24h

C. CONSTRAINT ANALYSIS

In actual SAR operations, every additional SAR unit constitutes additional operational cost. In order to be able to complete the SAR mission as quickly as possible while consuming as few human and material resources as possible, it is imperative to constrain the number of SAR units and the search time.

(1) The number of SAR units should be less than the number of SAR units that have the minimal search capability, which is still capable of completing the search task in the area.

(2) The time it takes for each SAR unit to reach the search area should be less than the total time spent completing the search task.

The specific formula can be expressed as:

$$s.t.\begin{cases} k \leq K_c \\ K_c = \prod \left[\dfrac{S}{V_{sa} \times W_a \times (T_v - t_a)} \right] \\ a = i \Leftrightarrow S_a = \min\limits_{0<i\leq n} S_i \\ t_i < T \end{cases} \tag{18}$$

where k is the number of selected SAR units; K_c is the upper bound on the number of SAR units; T_v is the survival time of the drowning personnel at the current sea temperature.

The survival time of drowning personnel is directly related to the sea surface temperature in the search area. The lower the sea temperature, the shorter the survival time of the human body in seawater. This paper analyzes and summarizes 43 typical accidents provided by China MSA, and combines the Maximum Observed Immersed Survival Time (MOIST) model [39] proposed by the US Coast Guard, from which are obtained a reference table of survival times for humans in seawater at different temperatures. This is shown in Table 1.

A curve fitting is performed according to the data in Table 1, from which it is found that each point in the table approximately satisfies the logarithmic function. Therefore, in this paper, the logarithmic curve is fitted to the data in the table within the 95% confidence interval, and the relationship between sea temperature and estimated survival time at

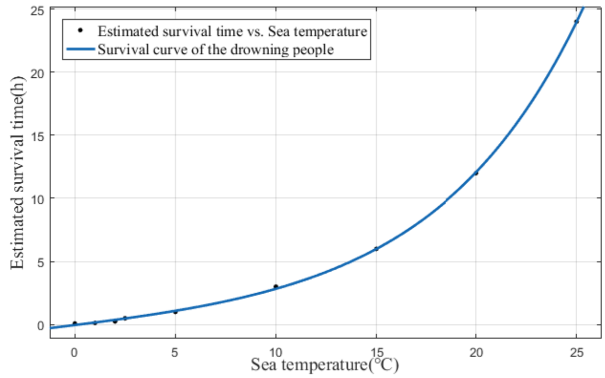


FIGURE 11. Relationship between sea temperature and human survival time.

0-25°C is obtained (as shown in Fig. 11). The function is as follows:

$$T_v = 0.80 \exp(0.1361 \times T_s) - 0.84 \exp(-0.1067 \times T_s) \tag{19}$$

where T_s is sea temperature and T_v is the estimated survival time.

The fitting effect is evaluated by two indicators: the sum of squares due to error (SSE) and the coefficient of determination (R-squared). The SSE is 0.07221, which is close to 0, proving that the model selection and fitting effect is sufficient. The R-squared is 0.9999, which is very close to 1. This shows that the function fit is very good, and that the dependent variable can be reliably interpreted in terms of the independent variable.

D. GENETIC SIMULATED ANNEALING ALGORITHM DESIGN

1) CHROMOSOME CODING

In the actual SAR process, the number of SAR resources available is different for accidents that occur in different locations, but the SAR mission has limited demand for SAR resources. Therefore, this paper adopts binary encoding method, where each chromosome represents an SAR resource deployment program. Each chromosome consists of n genes, where n is the number of available SAR units and each gene corresponds to a unit. The value of the i^{th} gene is $X_i (i \leq n)$, which is the decision variable of the resource scheduling model. When X_i is equal to 0, it means that the ship is not selected to participate in SAR operations. When X_i is equal to 1, it means that the ship is selected to participate in SAR operations. For example, if n = 16, the coding of a chromosome in the population is shown in Fig. 12.

The meaning of the code is that the 2nd, 7th, 10th, and 14th ships are selected to participate in the SAR mission.

2) INITIAL POPULATION GENERATION

In this paper, the initial population is generated in a random manner [40], and the population size represents the number of individuals in each generation. A lower population size

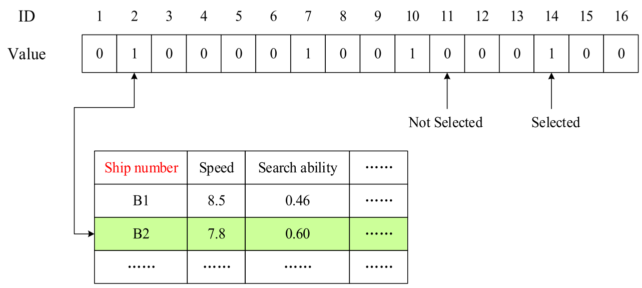


FIGURE 12. Chromosome coding diagram.

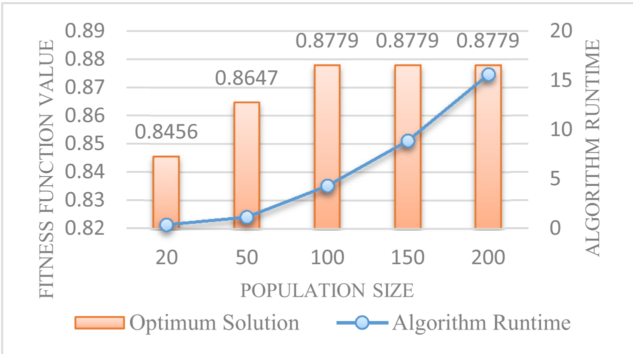


FIGURE 13. Comparison of optimal solutions and algorithm run times under different population sizes.

allows for a faster algorithm, but it also reduces the diversity of the population and make the algorithm premature. On the other hand, a large population reduces the algorithm's operational efficiency.

In general, the population size should be between 20 and 200. In light of this, this paper compares and analyzes the optimal solutions and algorithm run times under different population sizes (as shown in Fig. 13). It can be seen from Fig. 13 that the running time of the algorithm gradually increases with the increase of the population size. When the population size is 20 or 50, the algorithm produces a "prematurity" phenomenon and no global optimal solution is obtained. When the population size is 100, the algorithm obtains the global optimal solution and the run time is still short. Hence, a population size of 100 is used for the purposes of this article. In the initial population generation process, the SAR unit total constraint and search time constraint (as shown in formula 18) are followed to generate higher quality populations.

3) FITNESS FUNCTION DESIGN

In general, the fitness function is transformed by the objective function [41]. In this paper, the objective function is mapped to a fitness function that finds the maximum form and the function value is non-negative. The specific formula is as follows:

$$F(x) = maxf(x) \tag{20}$$

where $f(x)$ is the objective function value.

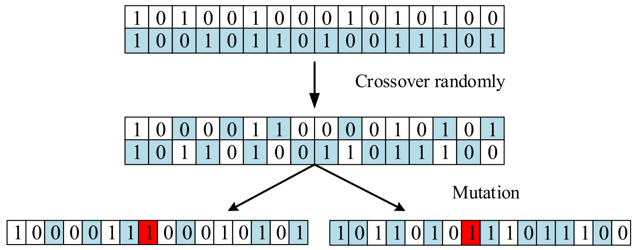


FIGURE 14. Crossover and mutation operation diagram, in which red genes are variant genes.

4) CHROMOSOME SELECTION, CROSSOVER AND MUTATION

Selection. The method of roulette is used for chromosome selection to ensure that chromosomes with higher fitness have higher probability of being selected as the next cross chromosome. This process allows for chromosome duplication.

Crossover. In the chromosome crossing process, a random crossover operator is used and the crossover probability is set to 0.8. The main idea of this operation is to randomly select genes on one parent chromosome and cross the genes at the corresponding positions on the other parent chromosome.

Mutation. After the crossover operation being completed, it is necessary to perform mutation operations on the crossed child chromosomes. That is, the gene number at a certain position on the chromosome is changed with a certain probability. The mutation probability is set to 0.2. Fig. 14 shows a schematic diagram of the crossover and mutation operator.

The crossover and mutated progeny population is fused with the paternal population and placed in a temporary population for optimization.

5) SIMULATED ANNEALING SELECTION OPERATOR

In the process of optimizing the temporary population, the annealing mechanism is introduced and the pairwise competitive selection operator is improved by the Metropolis principle of the SA. Therefore, the algorithm accepts not only the optimal solution but also some non-optimal solutions with a certain probability. In this way, the GA can avoid falling back into local optimal solutions to a large extent, and the probability of finding the global optimal solution is increased significantly while still maintaining search efficiency. The specific calculation formula is as follows:

$$P_i = \begin{cases} 1, & f(i) > f(j) \\ exp\left[\dfrac{f(i) - f(j)}{T}\right], & f(i) \le f(j) \end{cases} \tag{21}$$

$$P_j = \begin{cases} 0, & f(i) > f(j) \\ 1 - exp\left[\dfrac{f(i) - f(j)}{T}\right], & f(i) \le f(j) \end{cases} \tag{22}$$

where i and j are two individuals which are selected arbitrarily; P_i and P_j are the probability that two individuals enter the next generation population; $f(i)$ and $f(j)$ are the fitness values of two individuals; T is the temperature value.

For each selection, the temperature T is multiplied by the attenuation coefficient to cause the temperature to drop. When the temperature is lower than the lower limit of the set temperature, the algorithm stops.

VII. TASK ASSIGNMENT FOR SAR RESOURCES

Task assignment for selected SAR resources is a key part of SAR decision-making. In terms of space, the search area must be divided into multiple task areas; in terms of time, the temporality of the tasks should be considered, such that the areas with highest POS are preferentially searched. The regional task allocation algorithm proposed in this paper can take into account the temporal and spatial characteristics of task assignment, improve

SAR efficiency, and reduce the omission of targets. The principle of task assignment is as follows.

- The scheme adopts a staged search strategy, where the number of tasks in each phase is the same as the number of SAR units
- Each SAR unit searches for only one area at each stage.
- The task area of each SAR unit cannot exceed the allocated area of the SAR unit (area constraint)
- No task areas overlap (overlap constraint).
- Each stage of the search task ends at the same time.

A. GENERATION OF PROBABILITY DISTRIBUTION MAP

In this paper, the search area is divided into A × B grid cells of the same size [42]. The POC value of each grid cell is calculated according to formula (3), and the color is set according to the POC value for different grid cells, thereby generating a probability distribution map [43], [44]. The specific effect is shown in Fig. 15.

In the figure, The POC value gradually decreases from the middle of the area to the surrounding area. The deep red part has the highest POC, the light red part is the second, the yellow part has a lower POC, and the green is the lowest.

B. TASK ASSIGNMENT ALGORITHM FLOW

Considering the limited number of SAR units and the spatial-temporal characteristics of task assignment, this paper divides the search task into multiple stages. The goal of task assignment is to find a rectangular allocation scheme that maximizes the POS for each phase of the search task and satisfies the above allocation principle. The mathematical expression is as follows:

$$POS_K\,(A) = max\left(\sum_{i=1}^{k} POC_i \times POD_i\right), \quad S - \sum_{j=1}^{K-1} S_j > 0 \tag{23}$$

where A is a rectangular area, K indicates that the current stage is the Kth stage, k indicates the number of SAR units currently performing tasks, POC_i is the POC of the i-th SAR unit, POD_i is the POD of the i-th SAR unit, S is the entire search area, S_j is the search area of j-th stage.

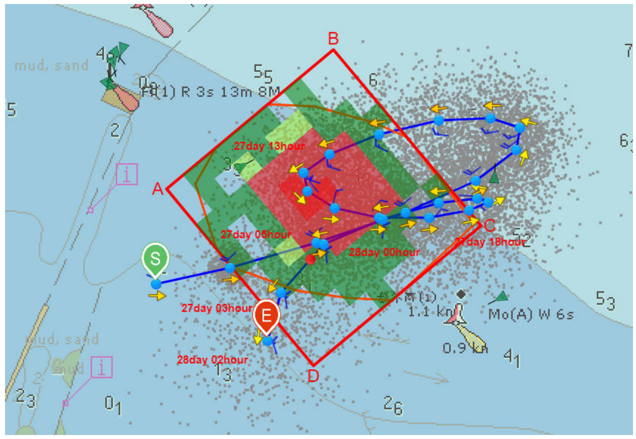


FIGURE 15. Probability distribution map of SAR targets in the search area.

TABLE 2. Accident ship information.

Ship name	MMSI	Ship type	Damage	Casualties
BI HAI 159	413332560	merchant ship	Safety	No
LUZHANYU 5186	900020670	fishing vessel	Flip	Four people missing

TABLE 3. The accident situation.

Accident location	On-site visibility	Medical level requirement	Average sea temperature
118°08'8"E 38°16'0"N	5-11nmi	0.8	12°C

According to the goal shown in formula (23), the following steps can be used to obtain the optimal task allocation scheme.

Step 1. Determine the initial search area. The scheme selects he cell with the largest POC as the initial search area according to the probability distribution map and calculates its probability of search success POS^1.

Step 2. Perform a regional expansion operation according to the "Folding Principle". Add one row or one column of cells along each edge based on the initial search rectangle, and recalculate the search success rate of the newly obtained region POS^2. Compare the size of POS^1 and POS^2. If $POS^2 > POS^1$, the new rectangle is used as the basis for the next fold. Otherwise, keep the original rectangle size and make the next fold.

Step 3. When the folding process described above satisfies the area constraint and the overlap constraint and the POS no longer increases, the folding process is terminated. The last returned rectangle is the first task area.

Step 4. Assuming that no target is found in the Kth task area under all area constraints, the POC of the searched area is blanked. Then follow steps 1-3 to re-determine the new search area.

Step 5. After the first stage regional task assignment is completed, update the location of the SAR unit and

TABLE 4. Ship performance parameter table.

Ship number	Ship location	Maximum speed (nmi/h)	Search ability (nmi^2/h)	Medical level
B1	117.8684°E/ 38.9298°N	8.5	0.46	0.50
B2	117.7884°E/ 38.9738°N	9.1	1.04	0.78
B3	117.8145°E/ 38.9380°N	7.9	0.80	0.90
B4	117.7691°E/ 38.9453°N	9.6	1.25	0.89
B5	118.2194°E/ 38.2776°N	6.2	1.85	0.65
B6	118.4559°E/ 38.9642°N	8.9	1.68	0.85
B7	118.5299°E/ 38.3483°N	9.5	1.80	0.68
B8	118.8196°E/ 38.2602°N	8.6	1.84	0.65
B9	118.7431°E/ 38.6104°N	8.5	1.98	0.74
B10	118.7462°E/ 38.5619°N	8.0	1.26	0.64
B11	117.9047°E/ 38.3661°N	10.1	0.57	0.70
B12	118.7680°E/ 38.9290°N	10.6	2.24	0.69
B13	118.6121°E/ 38.2981°N	7.5	1.20	0.50
B14	119.1489°E/ 38.2354°N	12.5	2.13	0.77
B15	118.0999°E/ 38.9035°N	10.5	2.67	0.50
B16	118.4482°E/ 38.4573°N	10.9	1.35	0.60

TABLE 5. Comparison of algorithm results at different time intervals.

Time interval	Medical requirement	Algorithm	Chromosome	SAR Ship	SAR time	POSSAR
10:00-13:00 (3 hours)	0.8	GSAA	0,0,0,0,1,0,0,0, 1,0,0,0,0,1,0,0.	B5, B9, B14	4.9625h	87.84%
		GA	0,0,0,0,1,0,1,0, 1,0,0,0,0,1,0,0.	B5, B7, B9, B14	4.2020h	86.53%
15:00-17:00 (2 hours)	0.8	GSAA	0,0,0,0,1,0,0,0, 1,0,0,0,0,1,0,0.	B5, B9, B14	4.6687h	87.79%
		GA	0,0,0,0,1,0,1,0, 1,0,0,0,0,1,0,0.	B5, B7, B9, B14	3.9884h	86.47%
22:00-23:00 (1 hour)	0.8	GSAA	0,0,0,0,1,0,1,0, 1,0,0,0,0,1,0,1.	B5, B7, B9, B14, B16	4.0314h	83.18%
		GA	0,0,0,0,1,0,1,0, 1,0,0,0,0,1,0,1.	B5, B7, B9, B14, B16	4.0314h	83.18%

probability distribution map and perform the second stage task assignment according to steps 1-4.

According to the above steps, the task allocation scheme of each SAR unit can be obtained. As shown in Fig. 16.

VIII. RESULTS

A. ACCIDENT CASE DESCRIPTION

This paper takes the Binzhou "6·27" "BI HAI 159" and "LUZHANYU5186" collision event as an example for the purpose of verifying the algorithm. This accident occurred at 3 a.m. on June 27, 2018. The Binzhou maritime rescue center received an alarm and launched an emergency response at 3:25. The specific accident information is shown in Table 2 and Table 3.

According to the drift prediction model, the collision point is used as a starting point, and the SAR target is subjected to 24-hour drift prediction. The search area is determined by the selected time interval, and the search route spacing of the ship is set to 0.2 nautical miles. According to the AIS information, there are 16 ships available and the performance parameters of each ship are shown in Table 4.

The parameters involved in the algorithm are as follows: the genetic algebra is 50, the population number is 100, the initial temperature of simulated annealing is 100, and the temperature attenuation coefficient is 0.85.

B. RESOURCE SCHEDULING RESULT

At present, the theoretical methods involved in the SAR resource scheduling problem mainly include analytic hierarchy process (AHP) [45], [46], linear programming theory, and combinatorial optimization theory. In the process of solving the problem, the fuzzy similarity preference [47], [48], AHP, GA and other methods are usually used to sort or combine the

TABLE 6. Comparison of algorithm results at different medical requirements.

Medical requirement	Time interval	Algorithm	Chromosome	SAR Ship	SAR time	POSSAR
0.8	15:00-17:00 (2 hours)	GSAA	0,0,0,0,1,0,0,0, 1,0,0,0,0,1,0,0.	B5, B9, B14	4.6687h	87.79%
		GA	0,0,0,0,1,0,1,0, 1,0,0,0,0,1,0,0.	B5, B7, B9, B14	3.9884h	86.47%
0.6	15:00-17:00 (2 hours)	GSAA	0,0,0,0,1,0,0,0, 0,0,0,0,0,1,1,0.	B5, B14, B15	4.4662h	97.80%
		GA	0,0,0,0,1,0,1,0, 0,0,0,0,0,1,1,0.	B5, B7, B14, B15	3.885h	97.55%
0.4	15:00-17:00 (2 hours)	GSAA	0,0,0,0,1,0,0,0, 0,0,0,0,0,1,1,0.	B5, B14, B15	4.4662h	97.80%
		GA	0,0,0,0,1,0,0,0, 0,0,0,0,0,1,1,0.	B5, B14, B15	4.4662h	97.80%

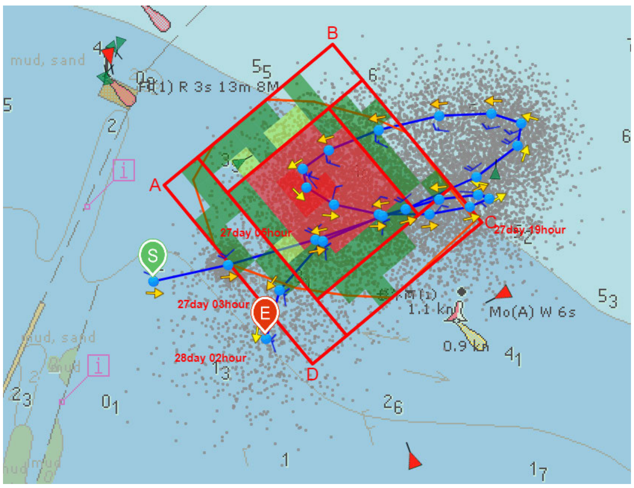


FIGURE 16. Regional task allocation scheme, in which the red vessel is the mission vessel and the rectangular zone is the mission area.

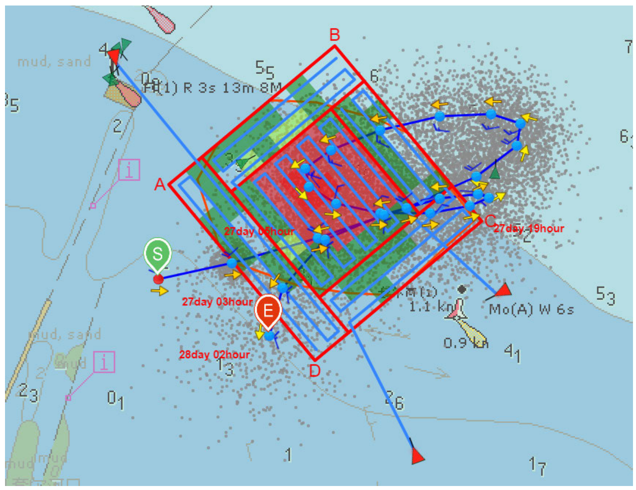
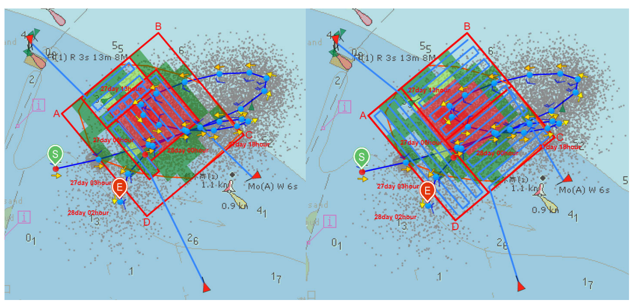


FIGURE 17. The search and rescue plan is visualized, and the blue line is the search route.



(a) (b)

FIGURE 18. (a) is a task assignment diagram based on the POS split algorithm; (b) is a task assignment diagram based on the region overall split algorithm.

available ships. Because of maritime SAR problems involve many factors such as time and cost, non-dominated sorting genetic algorithm II (NSGA-II) is often used to solve such multi-objective optimization problems [49]. In this paper, the optimal search theory and resource scheduling problem are combined to construct a ship scheduling model with a single goal of maximizing the POSSAR, and GSAA is used to solve the problem. The optimization effect of the proposed algorithm is verified by comparison with GA, because GA has good effect and wide application in solving single-objective and multi-objective resource scheduling models [50], [51].

According to the above description and AIS data, the optimal resource scheduling scheme solved by GSAA and GA can be obtained under different time intervals and medical requirements. The results are shown in Table 5 and Table 6.

The difference in time intervals determines the difference in the search area and therefore affects the POD. Different medical requirements determine the difference in POR. As can be seen from Tables 5 and 6, the POSSAR

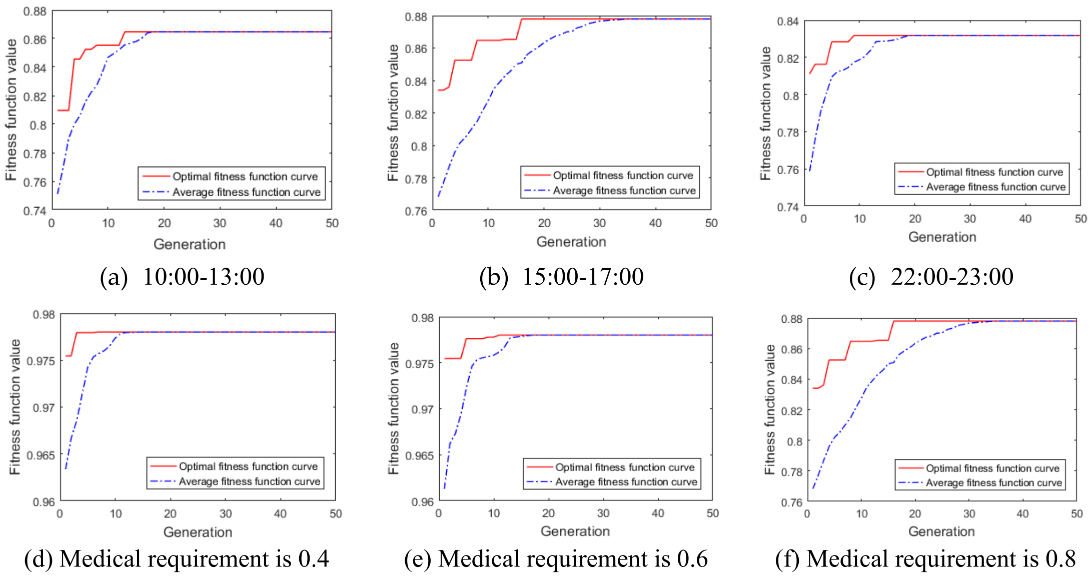


FIGURE 19. Comparison curve between average fitness function value and optimal fitness function value based on GSAA.

of the scheme obtained by GSAA is significantly greater than or equal to the POSSAR obtained by GA. The scheme obtained through GSAA has fewer SAR units and lower search cost, although its search time is longer. Therefore, considering the comprehensive consideration, the solution obtained through GSAA is better. Through the above analysis, the generalizability of the algorithm can be proved.

C. TASK ASSIGNMENT RESULT

Through the regional task allocation algorithm proposed in this paper, the search time, search area, area location, search mode and other important parameters can be obtained in the SAR decision process. The overall SAR plan is visualized as shown in Fig. 17. The ship closest to the search area will preferentially search the area with the highest POS. In the second stage of the search process, the ship closest to the current task area is preferentially selected from the available SAR units to shorten the search time. The three search units search five non-overlapping task areas in two stages, achieving full coverage of the search area.

The optimization of the task assignment algorithm in this paper is verified by comparing the POS splitting algorithm with the regional overall splitting algorithm. The specific plan is shown in Fig. 18.

It can be seen from the Fig. 18a that the red vessel on the far right is closest to the search area and can reach it first. Therefore, it searches a large region with a high POS in the middle of the overall search region. The three task areas did not achieve full coverage of the entire search area, and there was overlap between the three task areas. It can be seen from the Fig. 18b that the three task areas achieve full coverage of the entire search area, and the search area of the ship closer to the search area is larger.

IX. DISCUSSION

A. RESOURCE SCHEDULING RESULT ANALYSIS

1) ALGORITHM VALIDITY ANALYSIS

According to the calculation results, the optimal fitness value and the average fitness value comparison curve can be drawn at different time intervals and medical requirements. As shown in Fig. 19.

The analysis of Fig. 19 is as follows. Firstly, in the evolution process, the optimal fitness value is always higher than the average fitness value, both show an upward trend, and both converge after reaching a certain algebra. Secondly, there is no significant fluctuation in the average fitness curve. It shows that the proposed algorithm has better optimization ability and reflects the stability and effectiveness of the algorithm. Finally, the fitness function under different parameter conditions is consistent with the above analysis, which demonstrates the applicability of the algorithm.

2) ALGORITHM OPTIMIZATION ANALYSIS

The optimization of the algorithm is reflected in the capacity to identify the optimal solution and the speed with which that result is obtained. The optimization effect of the algorithm adopted in this paper can be obtained by comparison to the general genetic algorithm. The comparison assumes a medical need of 0.8 and a time interval of 15:00-17:00. As shown in Fig. 20.

It can be seen from the Fig. 20 that the fitness function curve based on the GA starts to converge from the 13th generation, and the fitness function curve based on the GSAA converges from the 16th generation. This shows that the GSAA does not lose too much search speed. The fitness function curve based on the GSAA converges to a higher fitness function value compared with the fitness function curve based on GA. This proves that the GSAA has better optimization

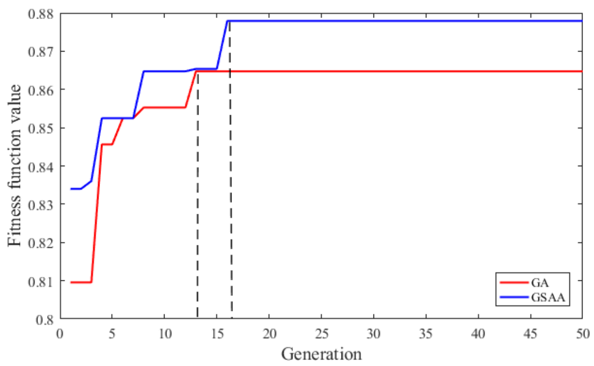


FIGURE 20. Comparison of the relationship between generation and fitness function values.

FIGURE 21. The national maritime search and rescue support system.

ability and global convergence effect. In summary, the SAR resource scheduling model based on GSAA proposed in this paper can obtain the SAR resource scheduling scheme with higher POSSAR.

B. TASK ASSIGNMENT RESULT ANALYSIS

The optimization of task assignment is reflected in the cooperation of SAR units and the efficiency of SAR. The POS splitting algorithm mainly allocates regional tasks according to the priority of tasks. The task area is divided according to the POS, and the area with higher POS is searched preferentially. However, the algorithm has the problem of often suggesting overlapping regions, which leads to failure to achieve full coverage of the search area, which in turn increases the possibility of target omission. The regional overall splitting algorithm mainly divides the search area according to the position and search ability of the ship. The area is calculated according to the arrival time and the search ability of each ship. The ship that first arrives in the search area searches for the nearest task area and has a large search area.

Both of the above solutions have their own advantages and disadvantages. Therefore, this paper proposes a scheme which avoids their shortcomings and retains their advantages, forming an optimal distribution scheme as shown in Figure 17. First of all, the scheme can preferentially search the area with the highest POS, which not only meets the principle of SAR operations but also improves SAR efficiency and shortens SAR time. Secondly, the total mission area of all SAR units can cover the entire search area, which can reduce the probability of target omission. Finally, there is no overlap between task areas, which avoids invalid searches and saves both time and cost.

At present, the algorithm proposed in this paper has been applied to the national maritime search and rescue support system and provides SAR services for the sea areas in China and Southeast Asia. It has been put into service more than a thousand times, and the effect is remarkable. The platform design is shown in Fig. 21.

X. CONCLUSIONS

In this paper, the key technologies involved in the process of forming maritime SAR emergency response plans are analyzed in detail, and the maritime SAR decision problem is decomposed into three sub-problems: SAR area determination, SAR resource scheduling, and SAR task assignment. The main contributions of this paper are as follows.

(1) The theory of optimal search at sea has been improved. The concept of POSSAR is proposed by introducing the POR and used as the objective function of the resource scheduling model. This model takes life-saving assistance as a priority factor, which is more in line with the actual SAR operations, and the resource scheduling plan obtained is more reasonable.
(2) The resource scheduling model is solved by GSAA, which can find the global optimal solution while ensuring the search efficiency, and avoid falling into the local optimal solution.
(3) A new regional task assignment algorithm based on space-time characteristics is designed. The algorithm produces a plan which covers the entire search area while considering task priority and without overlapping task areas. This not only reduces the probability of missing targets and improves SAR efficiency, but also reduces redundant searches, and thus saves SAR time and cost. Moreover, the algorithm performs the staged planning of the search task, which improves the synergy between the SAR units.
(4) Through various intelligent algorithms, the main problems in each part of the maritime SAR decision are solved, and the complete and optimized decision-making scheme is obtained quickly and intelligently, which not only shortens the accident response time, but also improves the efficiency of SAR.

Through the example verification, the decision algorithm for the SAR emergency response plan proposed in this paper shows obvious optimization, which can provide reference for the formulation of future maritime SAR emergency response plans.

In the future, we will begin to study some of the unresolved decision-making issues (e.g., dynamic adjustment of decision-making programs, collaborative SAR of aircraft and ships, etc.). At present, there are two main ideas: (1) Through Adversarial Networks, optimizing SAR decisions by imitating successful SAR operations; (2) using Reinforcement

Learning to realize interaction between agents (SAR units) and the environment (SAR environment), thereby optimizing the behavior of agents.

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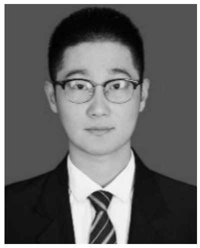

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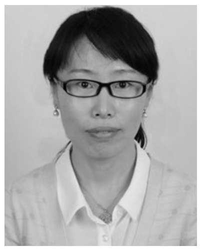

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