Modern Management based on Big Data III
A.J. Tallón-Ballesteros (Ed.)

doi:10.3233/FAIA220120

Optimization of Maritime Search and Rescue Resources Selection Based on Response Threshold Ant Colony Algorithm

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Abstract. The timeliness and severity of maritime search and rescue (MSAR) determine that the resource selection should be fast and optimized as much as possible. At present, there is no intelligent optimization method to assist decision-making, which is suitable for the actual characteristics of MSAR. In this paper, the optimization problem of MSAR resource selection is abstracted into a multi-objective optimization problem. Considering the needs of actual MSAR resources, the response threshold model is introduced to improve the ant colony algorithm. It can effectively solve the situation that the ordinary optimization algorithm is easy to fall into the local optimal solution and ignore the better resources. The research work of this paper is divided into three parts: model construction, model solution and model verification. Firstly, a multi-objective optimization model with five practical constraints is constructed to minimize the search time and maximize the average utility of resources. Then, the response threshold model considering the actual resource demand is used as the heuristic information in the ant colony algorithm. The stimulus model and threshold model in the response threshold model represent the ability of resources to perform tasks and the threshold of resources to perform tasks respectively, so as to improve the efficiency and speed of the algorithm. Finally, the algorithm is verified and compared through an example. The experimental results show that the average resource utility of this algorithm is 20.6% higher than that of the basic ant colony algorithm, and the MSAR success rate is also improved, which verifies the effectiveness of this method.

Keywords. Maritime search and rescue, resource optimization, ant colony algorithm, response threshold mode

1. Introduction

China is a large marine country with 18000 kilometers of coastline and 3 million square kilometers of sea area. With the development of China's marine industry, marine activities are becoming more and more complex. MSAR accidents occur frequently. In China, there are many MSAR cases every month, resulting in dozens of deaths. Therefore, improving China's MSAR capability has become a very realistic and challenging problem.

At present, relevant research on MSAR methods has been carried out at home and abroad. Among them the representative is the Search and Rescue Manual "international

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aviation and MSAR Manual" jointly launched by the International Maritime Organization (IMO) and the International Civil Aviation Organization (ICAO) in 1998 [1]. This manual is summarized and formed on the basis of part I, II and III [2-4] of the search theory. Published by the anti-submarine military operations research group composed of Koopman and his colleagues. Literature [5-8] studies the optimization model and method of rescue ships by using classification analysis, modern decision-making theory and fuzzy mathematics evaluation method. Literature [9-10] studies how to calculate the drift of maritime distress targets with wind and current, determine the search area and range and the optimal search mode.

The research on the resource selection and optimization scheme of MSAR is basically the analysis and evaluation of a single MSAR force. In reality the MSAR behavior is often accompanied by a variety of MSAR forces at the same time. In order to adapt to this change, it is not common to use intelligent optimization algorithm to solve MSAR problems. The only intelligent optimization algorithms used in solving MSAR resources simply apply the basic algorithm framework. For example, common optimization algorithms include genetic algorithm [11-13], DE differential evolution algorithm [14], ant colony algorithm [15-16], etc. They do not consider the actual background needs to design and improve the algorithm, which will lead to insufficient optimization of the final generated resource scheme [17].

Ant colony algorithm is a population intelligent algorithm proposed by Italian scholar Dorigo m et al. [18] in the 1990s. It has strong robustness and is easy to be combined with other optimization algorithms. With the development of the algorithm, ant colony algorithm has been applied to many fields such as job scheduling and path planning [19-22]. However, the common ant colony algorithm does not better consider the resource requirements of MSAR. Although it realizes the solution of the multi-objective optimization model, it is prone to problems such as slow convergence speed, easy to fall into local optimization, long search time and so on.

In recent years, the combination of response threshold model and intelligent optimization algorithm has made it possible to optimize the selection of MSAR resources. The response threshold model is a task distribution model [23-25] proposed to simulate the social division of labor mechanism of insects. According to the perceived information of the task and the internal threshold of the individual undertaking the task. The model determines the probability of the individual response to the task. It reveals the self-organizing labor division mechanism of social insects, and explains the relationship between individual adaptability and system robustness. It can accelerate the convergence speed of ant colony algorithm according to the actual information of the problem and avoid falling into local optimal solution. Wang yingcong [26] and others combined the artificial bee colony algorithm with the response threshold model to prove the effectiveness of the artificial bee colony algorithm based on the stimulus response division mechanism. A.P. Kanakia [27] proposed a task allocation strategy of multi-agent system based on response threshold. Therefore, it is feasible to introduce the response threshold model into the solution of the optimization problem of MSAR resource selection. But it is difficult to better map the elements of the response threshold model with the actual elements of MSAR emergency decision-making. In order to more truly reflect the actual situation of MSAR and better apply the optimization algorithm in MSAR emergency decision-making. This paper innovatively introduces the response threshold model to solve the problems of slow convergence speed and easy to fall into local optimization of ant colony algorithm. An improved ant colony algorithm based on response threshold model is proposed. It can select better resources while optimizing the objective function, improve the speed of resource selection, and avoid the omission of better resources. To better assist decision makers in making decisions on the selection of MSAR resources selection and improvement in MSAR success rate. The paper is mainly divided into three parts. Firstly, the MSAR resource selection model based on multi-objective optimization is constructed. Then the ant colony improvement algorithm process based on response threshold model is described. Finally an example is compared and analyzed.

2. Problem Analysis and Modeling

2.1. Modeling Assumptions

This paper is conducted under the following assumptions:

- All persons in distress shall be evenly distributed in the search area;
- This paper only considers the situation of aircraft search and ship rescue;
- It is assumed that the time when all MSAR aircraft cover the specified search area is the time of the search phase;
- It is assumed that the performance information of various aircraft under different sea conditions has been known.

2.2. Modeling Establishment

1) Decision variable analysis

MSAR operations are usually carried out in very complex situations. There are many factors affecting MSAR operations and many model input conditions to be considered. Basic information includes: information related to people in distress; information related to the marine environment during MSAR; the impact of the environment on MSAR operations; dangerous situations that MSAR personnel may face.

Relevant parameters and their specific descriptions are shown in Table 1 below:

Table 1. Specific Description of relevant parameters.

Parameters	Description
B	Sea state level during MSAR (level 1-9)
d_m	Distance from military MSAR force to search area (n miles)
d_s	Distance from professional MSAR force to search area (n miles)
d_l^i	Distance from local MSAR force to search area (n miles)
S	Area to be searched$(n\ mile)^2$
N	Number of people in distress (person)
V_i	Maximum speed of resource i (kn)
n_i	Available quantity of resources
cap_j	Aircraft $j's$ search capability $(n\ mile^2/h)$
p_j	Probability of aircraft j finding target
sal_k	Average fishing time of ship k (h)
c_k	The upper limit of the number of people the ship k can carry
h_0	Average maximum waiting time of people in distress

Decision variable: the optimization scheme for the selection of MSAR resources, which should include the description of the types and quantity of resources. Therefore, the mathematical expression of MSAR resource scheme is:

$$X = (x_1, x_2, \ldots, x_M) \tag{1}$$

Where, x_i represents the number of resources in the scheme. If x_i is 0, it means that the MSAR scheme resource i is not involved.

2) Objective function analysis

Objective 1: minimize the search time: the total search time T_s refers to the maximum working time of various resources required to cover the area to be searched. The composition of the total search time is shown in Figure 1.

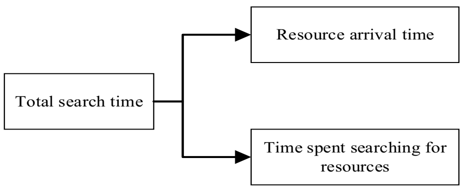

Figure 1. Search time composition.

For aircraft, the time spent on the road needs to be considered. Therefore, the time taken by the aircraft i on the road is t_i

$$t_i = \begin{cases} \frac{d_m}{V_i}, i\ belongs\ to\ the\ military\ search\ and\ rescue\ force \\ \frac{d_s}{V_i}, i\ belongs\ to\ the\ professional\ search\ and\ rescue\ force \end{cases} \tag{2}$$

The actual search time of the aircraft i in the total search time is:

$$\overline{t_s} = T_s - t_i \tag{3}$$

The sum of the search area of all aircraft involved in MSAR should be equal to the total area to be searched:

$$\sum_{i=1}^{J} (T_s - t_i) \cdot cap_i \cdot x_i = S \tag{4}$$

$$MIN(T_s) = \frac{S + \sum_{i=1}^{J} t_i cap_i x_i}{\sum_{i=1}^{J} cap_i x_i} \tag{5}$$

Objective 2: maximize the average resource utility: the average resource utility refers to the average value of the utility brought by the resources participating in MSAR. The utility of resources can be measured by the probability of success (POS) [17].

Since the area to be searched is known in this model, assuming that all the people in distress are in the area to be searched, that is $\mathrm{POC} = 1$. The probability of discovery refers to the probability that the person in distress is included in the search area of a search subject (the search subject in this paper is an aircraft) and the search subject finds the target.

$$POS = POD \times POC = POD = \sum \frac{S_i}{S} P_i \tag{6}$$

According to formula (6), the average utility of resources is:

$$MAX(E) = \frac{\sum \frac{S_i}{S} P_i}{\sum_{i=1}^{J} x_i} \tag{7}$$

In this paper, the multi-objective problem containing the above two objectives are transformed into a single objective problem, and the model is as follows:

$$MIN\left(w_{T_s} \cdot T_s + w_E / E\right) = w_{T_s} \cdot \frac{S + \sum_{i=1}^{J} t_i cap_i x_i}{\sum_{i=1}^{J} cap_i x_i} + w_E \Big/ \frac{\sum \frac{S_i}{S} P_i}{\sum_{i=1}^{J} x_i} \tag{8}$$

Where w_{T_s} and w_E is the weight of target T_s and target E. In the later example, by comparing w_{T_s} and w_E to adjust the parameters, so that the goal of the single objective problem is better.

3)Constants analysis

Due to the limitations of realistic environmental conditions and the attributes of resources. There are certain constraints in the selection and optimization of MSAR resources. The following are the constraints summarized in this paper.

(1) Resource quantity constraint
There is an upper limit on the number of resources available. Therefore, the following constraint should be met in the scheme:

$$0 \le x_i \le n_i, n_i \text{ is available quantity for resource } i, i = 1,2,3,\cdots,M \tag{9}$$

(2) Maximum sea state constraint for safe driving of resources
In order to ensure the safety of MSAR resources, it is necessary to ensure that the resources performing MSAR tasks carry out sea operations under the maximum allowable sea conditions.

$$B_i \ge B, B_i \in \{1,2,\cdots,9\}, i = 1,2,\cdots,M \tag{10}$$

(3) Upper limit of ship accommodation
In order to ensure safe driving, different ships hold different numbers of people.

$$N \le \sum c_i \,, i \in \text{involved resources} \tag{11}$$

(4) The time for MSAR resources to reach the specified search area shall not exceed the total MSAR time constraint
Each MSAR resource must arrive at the scene before completing the search task to have the opportunity to participate in the search operation:

$$t_j < T_s \text{ and } t_k < T_r \tag{12}$$

(5) The person in distress was still alive when rescued
The survival level (POL) of the MSAR target is positive. Survival level represents the survivability level of people in distress when they are successfully rescued. It is directly related to MSAR time and sea conditions [28]. Therefore, this paper uses MSAR time and the longest waiting time of MSAR targets to measure the survival level. The expression of POL is as follows reference [29]:

$$POL = 1 - \frac{E_r}{h_0 + \Delta h} \tag{13}$$

3. Model Solving

There are many kinds and quantities of resources involved in MSAR, especially major MSAR. MSAR resource selection is a NP-hard problem. MSAR requires high timeliness, it is difficult to quickly formulate an efficient resource selection scheme through manual and other ordinary methods. Therefore, this paper adopts ant colony algorithm based on response threshold model. In addition to making the intelligent optimization algorithm more in line with the actual needs of MSAR resources. It can also overcome the defects of ordinary ant colony algorithm, such as slow convergence and easy to fall into local optimal solution.

Ant colony algorithm absorbs the foraging behavior characteristics of real ant colonies in nature. It is a distributed multi-agent system with strong robustness. However, when the solution space is complex and multi-modal, it is easy to fall into local extremum and premature. So it is impossible to generate high-quality offshore resource selection schemes.

The response threshold model is closely related to two factors. One is the stimulus intensity s associated with a specific task It can be expressed as the number of encounters, the concentration of chemicals or other quantifiable clues that can be perceived by individuals. The other is the response threshold θ. It describes the internal tendency of individuals to perform tasks. The smaller the threshold, the stronger the tendency. Specifically, when $s \ll \theta$, the response probability is low, and when$s \gg \theta$, the response probability is high. A cluster of corresponding functions meeting the above requirements $T_\theta(s)$ is defined as:

$$T_{\theta_{ij}}(s_j) = \frac{s_j^n}{s_j^n + \theta_{ij}^n} \tag{14}$$

Where n is a constant, which determines the slope of the response threshold curve.

The performance information of resources is introduced into the ant colony algorithm by responding to the stimulus and threshold in the threshold model. It can accelerate the convergence speed of the ant colony algorithm according to the actual information of the problem and avoid falling into the local optimal solution.

In this paper, a single resource performing the task is modeled as an intelligent individual. Through the response threshold model, the response probability of selecting resources to perform the task is determined. According to the resource performance, the more suitable resource is to perform a task, the greater the response probability of the corresponding task. Replace the heuristic information in the ant colony algorithm with the response probability of the resource to the task obtained from the response threshold model. Update the pheromone and threshold quantity according to the advantages and disadvantages of the scheme obtained by the ant colony algorithm to further update the response probability. The better the scheme is, the greater the pheromone concentration and response probability of the resource selected in the scheme, and the better resources will be given priority in the next iteration. In this way, the resource performance and actual environment requirements can be taken into account in the ant colony algorithm, and the optimal solution can be found faster and better.

The response probability of resources to tasks is determined by two response functions in the response threshold model. One is used to determine the stimulus of resources. Another response function is used to determine the response threshold of the task to resources.

Therefore, this paper adopts ant colony algorithm based on response threshold model to solve the problem of MSAR resources. The specific process is shown in Figure 2.

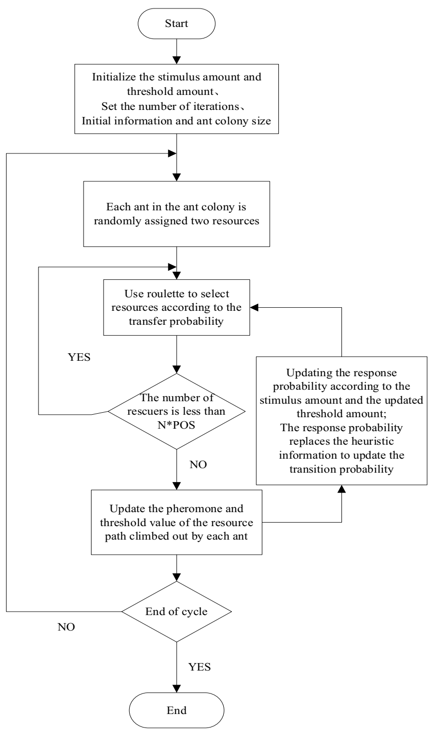

Figure 2. Algorithm flow chart.

3.1. Response Threshold Model for MSAR Resource Designs

Due to the different performance of different types of resources, the efficiency of completing MSAR is also different. Therefore, this paper reflects the performance of different resources through the factors such as the maximum number of ships, the average salvage time of ships, the MSAR sea conditions, the search ability of aircraft, the probability of aircraft discovery and so on.

In order to consider the above factors reflecting the resource performance into the ant colony algorithm. Select the better resources to participate in the MSAR in combination with the MSAR task. This paper determines the initial response probability of the resources to the MSAR task by the resource performance. In the iterative process, when the resource performance is better and the response threshold of its corresponding task is lower, the response probability is greater and the probability of participating in the task is greater. Therefore, the response threshold model can better meet the resource needs and select better resources.

Using the response threshold model, we need to determine the stimulus s of resources and the response threshold θ of resources to tasks. Through the modeling and analysis of MSAR and the introduction of response threshold model, two functional models need to be determined

1)Stimulus model based on the performance of MSAR resources

The stimulus model reflects the ability of resources to perform tasks. The greater the stimulus, the better the ability of resources to perform tasks. According to equation (14), when the response threshold is certain, the greater the stimulus, the greater the response probability of resources to tasks. Therefore, the higher the probability of selecting better resources, which meets the needs of maritime resource selection.

For different resources (aircraft and ship), due to the different tasks they perform and the different performance parameters they need. The corresponding models will be different when calculating their stimulus.

For ships, the greater the maximum number of people, the shorter the average salvage time, the higher the level of MSAR sea conditions and the shorter the time to reach the area to be searched, the better the resource performance, and the corresponding stimulus s_j should be larger. The greater the stimulation of ship resources j to the task, the greater probability to participate in the rescue action. The stimulation model is shown in formula (15):

$$s_j = \frac{\frac{c_j}{t_j \cdot sal_j \cdot 100} + B_j}{10}, j \in \text{allocable ship} \tag{15}$$

For the aircraft, the stronger its performance search ability, the greater the probability of finding the target, the higher the level of MSAR sea conditions, and the shorter the time to reach the area to be searched. It means the better its performance s_j should be larger. The greater the stimulation of aircraft resource j to the task, the greater probability to participate in the search action. The stimulation model is shown in formula (16):

$$s_j = \frac{\frac{cap_j \cdot P_j}{t_j \cdot 1000} + B_j}{10}, j \in \text{allocable aircraft} \tag{16}$$

2)Threshold quantity model based on cooperation degree of MSAR resources

The resource matching degree refers to the minimum capacity demand or threshold of the task for resources. According to equation (14), when the stimulus amount is certain, the smaller the threshold value the greater the response probability of resources to the task. Therefore, the higher the probability of selecting resources with better performance of tasks, which meets the needs of maritime resource selection.

Coordination of MSAR resources θ_{ij} indicates the probability that resource j also participates when resource i participates in the MSAR mission. In the iterative process, if resource i and resource j appears more times in the optimal solution. The smaller the corresponding θ_{ij} will be, the lower the response threshold of resource i and resource j to the task. Because the number of occurrences of resource i and resource j in the optimal solution means that resource i and resource j cooperate well. Resource i or resource j can better complete the MSAR task, the lower the threshold of participating in the MSAR task should be. Under the ethnic reward and punishment mechanism, the threshold will be reduced when individuals successfully perform the task, the threshold increases when the task is not successfully executed. The threshold value is expressed by the resource matching degree, which can avoid the situation that the solution falls into local optimization due to the prominence of a certain resource.

The threshold quantity model is shown in equation (17):

$$\theta_{ij}^{g} = \theta_{ij}^{g}(x) = \theta_{ij}^{g-1} - \frac{ij_{size}^{g-1}}{tabu_{size}^{g-1} \cdot w_{\theta}} \tag{17}$$

Where ij_{size}^{g-1} represents the number of occurrences of resource i and resource j in the g-1optimal solution. $tabu_{size}^{g-1}$ represents the number of resources in the g-1 generation optimal solution. w_{θ} is an adjustment parameter that controls the change rate of θ_{ij}^{g}.

3.2. Ant colony algorithm based on response threshold model

1)Basic idea of ant colony algorithm

The mechanism of ant colony optimization (ACO) is to simulate the behavior of ants in the process of looking for food. When ants are looking for food, they can release a specific pheromone secreted by ants on the their path. So that other ants can detect and affect their behavior within a certain range (tend to choose the path with high pheromone concentration). When more ants walk on a path, the more pheromones left on this path, the higher the pheromone concentration. It makes the following ants more likely to choose this path. In the process of continuous repetition, the path with the highest pheromone concentration is the optimal foraging path [30].

2)Ant colony algorithm based on response threshold model

In this paper, after combining the response threshold model with ant colony algorithm, the relevant formulas and some parameters are as follows. The state transition probability of ant k from node i to node j at time t is shown in (18):

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot \left[T_{\theta_{ij}}(s_{ij})\right]^{\beta}}{\sum_{s \in allowed_k} [\tau_{ij}(t)]^{\alpha} \cdot \left[T_{\theta_{ij}}(s_{ij})\right]^{\beta}}, j \in \text{Node that the } k \text{ ant select} \\ 0, \text{others} \end{cases} \tag{18}$$

Where $T_{\theta_{ij}}(s_{ij})$ is the response model that acts as heuristic information in ant colony algorithm, τ is pheromone, α is pheromone adjustment coefficient, and β is heuristic information adjustment coefficient.

The pheromone left by the k ant on the path (i,j) is shown in formula (19):

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{L_k}, \text{The } k \text{ ant passes through } (i,j) \text{ in this cycle} \\ 0, \text{others} \end{cases} \tag{19}$$

The total amount of pheromones left by m ants on the path (i,j) is shown in equation (20):

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{20}$$

Where $\Delta\tau_{ij}$ represents the pheromone increment on the path (i,j) in this cycle, and the initial time is $\Delta\tau_{ij}$=0。 $\Delta\tau_{ij}^{k}$ represents the amount of information left by the k ant on the path (i,j) in this cycle.

After all ants complete a cycle, they need to update the residual pheromone on the path, that is, the volatilization of pheromone. The pheromone on each path (i,j) is adjusted according to formula (21):

$$\tau_{ij} = (1-\rho)\tau_{ij} + \Delta\tau_{ij} \tag{21}$$

Where ρ is the volatilization coefficient of pheromone.

(1) Select MSAR resources

In ant colony algorithm, there are many ways for ants to choose the next resource. This paper selects the classical roulette method to choose.

The probability of ants selecting the next resource adopts the state transition probability introduced above. Although the probability of selecting each resource is obtained, due to the diversity of ant colony algorithm, it is necessary to ensure that other resources also have the opportunity to be selected. If only resources with high probability are selected, it will become a greedy algorithm. Therefore, choose the way of roulette. First, obtain the probability value of each resource, and sum these probabilities to the total probability value. Then randomly generate a random number between 0 and the total probability range. Then the probability value of each resource is successively subtracted until it is negative to get the next selected resource. Repeat the same operation until the cycle end condition is reached.

(2) Generate MSAR resource scheme

For a MSAR resource selection scheme, all resources can only be accessed once. So the accessed resources need to be stored in the taboo table to avoid repeated access. Among all the accessible resources, we should also consider the performance of the resource, and judge whether the resource can be added to the taboo table according to the state transition probability. The resources of the final taboo table are the resources that ultimately participate in the task, that is, the taboo table is the obtained MSAR resource selection scheme.

4. Experiment

4.1. Experiment description

An accident occurred in a sea area of the Yellow Sea. A merchant ship with 70 people accidentally hit a reef, lost power and was in danger of overturning. The personnel released life-saving equipment and abandoned the ship to actively save themselves. However, due to the bad sea conditions, the drowning personnel had a wide floating range and complex injuries, so it was in urgent need of external rescue. The distance between the place of distress and the nearest professional MSAR center and naval MSAR center is 90 and 120 nautical miles respectively. There are five fishing boats and merchant ships available near the sea area. Moreover, some professional rescue ships and aircraft in the professional MSAR center are performing daily patrol tasks outside, and a small amount of equipment in the naval MSAR center is under maintenance and is not available. It is measured that the area to be searched is 800 (n mile^2), the current sea state is level 4 [31], and the longest waiting time for people under level 4 sea state is 5 hours. The performance information of professional MSAR forces is shown in Table 2, the performance information of military MSAR forces is shown in Table 3, and the performance information of MSAR forces of passing ships is shown in Table 4. The distance between professional MSAR forces and the accident point is 90 (n miles), and the distance between military MSAR forces and the accident point is 120 (n miles).

This paper adopts the ant colony algorithm based on the response threshold model, so the experimental parameters of the basic ant colony algorithm and the parameters of the threshold model will be used in this experiment. Parameter settings are shown in Table 5. The programming language used in this experiment is Java, the code writing tool is MyEclipse 2017 CI, and the running environment is Windows10.

Table 2. Performance information of professional MSAR forces.

Type	Sea state restrictions	Speed (n mile/h)	Capacity	Search ability (n mile^2/h)	Discovery probability	Available quantity	Average rescue time
Helicopter A	Level 4	220	0	100	0.95	2	0
Helicopter B	Level 3	170	0	90	0.7	2	0
Fixed wing aircraft A	Level 4	300	0	130	0.9	3	0
Fixed wing aircraft B	Level 5	620	0	240	0.91	1	0
Huaying rescue boat	Level 4	39	3	0	0	4	0.02
Professional rescue ship	Level 4	27	15	0	0	2	0.06
Fast rescue boat	Level 4	32	7	0	0	3	0.03
Large rescue ship	Level 5	22	12	0	0	1	0.08

Table 3. Performance information of military MSAR forces.

Type	Sea state restrictions	Speed (n mile/h)	Capacity	Search ability (n mile^2/h)	Discovery probability	Available quantity of resources	Average rescue time
Helicopter C	Level 4	280	0	120	0.8	2	0
Transport plane	Level 4	550	0	200	0.95	2	0
Fixed wing aircraft C	Level 3	700	0	270	0.85	0	0
Hospital ship	Level 5	18	40	0	0	1	0.12
Rescue ship	Level 3	35	8	0	0	3	0.01
China high speed rescue ship	Level 5	40	20	0	0	2	0.08

Table 4. Performance information of local MSAR forces.

Type	Sea state restrictions	Speed (n mile/h)	Capacity	Available quantity of resources	Average rescue time	Distance from the ship to the place of distress (n mile)
Fishing boat A	Level 4	12	10	1	0.04	30
Fishing boat B	Level 5	10	9	1	0.01	40
Fishing boat C	Level 5	9	15	1	0.05	80
Merchant ship A	Level 4	32	25	1	0.15	120
Merchant ship B	Level 4	39	10	1	0.10	150

Table 5. Algorithm meaning and value of parameters.

Parameter meaning	Parameter value
Initial population sizeP_0	33
α(Pheromone adjustment coefficient)	0.6
β (Heuristic information adjustment coefficient)	0.8
ρ(Pheromone Volatilization Coefficient)	0.4
n(Determines the slope of the response threshold curve)	2
w_{T_s}	0.9
w_E	0.1
θ_{ij}_max(When there is resource i, the maximum response threshold that resource j also participates in)	1
θ_{ij}_min(When there is resource i, the minimum response threshold that resource$j$ also participates in)	0.1
MAX_GEN (Maximum number of iterations)	1100
τ_{min} (Pheromone minimum)	0.2
τ_{max} (Pheromone maximum)	0.8

4.2. Result Analysis

Substituting the above information into the ant colony algorithm based on the response threshold model and the basic ant colony algorithm can obtain the MSAR resource selection scheme shown in Table 6 and Table 7 respectively.

Figure 3 shows the comparison between ant colony algorithm in this paper and basic ant colony algorithm in iterative objectives. The basic ant colony algorithm can reach the optimal value in about 120 generations. While the ant colony algorithm in this paper has reached a stable state in about 55 generations and converged quickly to the ideal value. Moreover, the final target value of the algorithm in this paper is 1.631, which is better than the target value of 1.636 calculated by the basic ant colony algorithm. Figure 4 shows the comparison between the algorithm in this paper and the basic ant colony algorithm in the average utility of iterative resources. It can be seen from Figure 4 that the average utility value of resources obtained by using the algorithm in this paper is 0.0931. It is better than the average utility value of resources obtained by using the basic ant colony algorithm of 0.0772. Figure 5 and Figure 6 respectively show the comparison of iterative search time and search success rate between the algorithm in this paper and the basic ant colony algorithm. Although the search time of 1.512h obtained by this algorithm is longer than that of 1.041h obtained by the basic ant colony algorithm. The search success rate of 0.931 obtained by this algorithm is higher than that of 0.927 obtained by the basic ant colony algorithm. Moreover, the search time obtained by this algorithm is much shorter than the longest waiting time 5h of people in level 4 sea conditions.

Through the above comparative analysis, it can be seen that the ant colony algorithm in this paper converges faster than the basic ant colony algorithm and is closer to the ideal solution. When the search time meets the MSAR, the average resource utility of the ant colony algorithm based on the response threshold model is 20.6% higher than that of the basic ant colony algorithm.

Table 6. The paper algorithm resource plan display.

Composition of resource scheme		
Professional rescue force	Military MSAR force	Local MSAR force
Helicopter A x1	Transport plane x2	Fishing boat B x1
Fixed wing aircraft A x1	Hospital ship x1	
Fixed wing aircraft B x1	China high speed rescue ship x1	
Fast rescue boat x1		
Professional rescue ship x1		

Table 7. Basic ant colony algorithm resource plan display.

Composition of resource scheme		
Professional rescue force	Military MSAR force	Local MSAR force
Helicopter A x1	Transport plane x2	Fishing boat A x1
Fixed wing aircraft A x2	Hospital ship x1	
Fixed wing aircraft B x1	China high speed rescue ship x1	Merchant ship A x1
Huaying rescue boat x1		
Professional rescue ship x1		

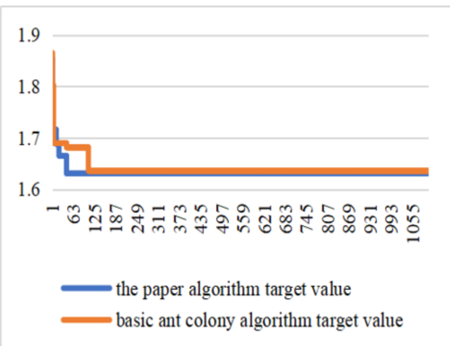

Figure 3. Target value comparison chart.

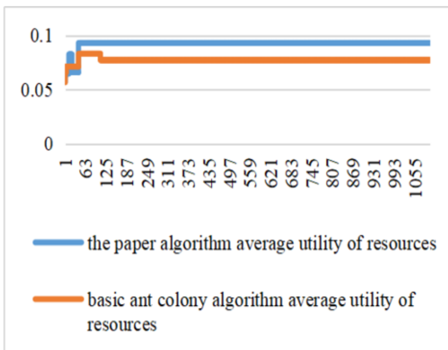

Figure 4. Average utility of resources comparison chart.

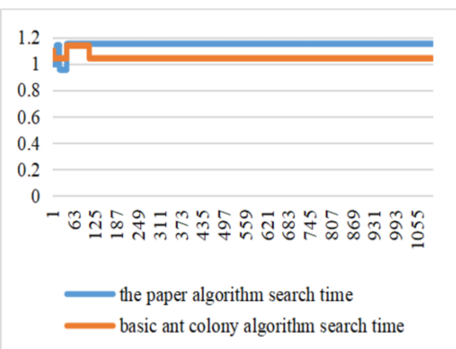

Figure 5. Search time comparison chart.

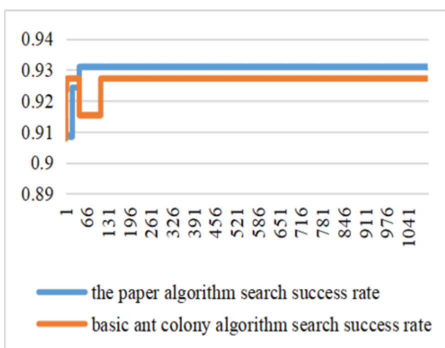

Figure 6. Search success rate comparison chart.

5. Conclusion

For the future development of intelligent emergency decision support system. It has important theoretical value and practical guiding significance for improving the timeliness and applicability of the optimization algorithm in MSAR emergency decision-making. In this paper, the optimization problem of MSAR resource selection is abstracted into an operation planning problem. A multi-objective optimization model and a response threshold model considering the actual resource demand are constructed. The response threshold model is combined with ant colony algorithm, and the ant colony algorithm based on the response threshold model is used to solve the model. Through the research of this paper, it effectively solves the problems of slow convergence speed of ordinary optimization algorithm in solving the optimization problem of MSAR resource selection and easy to fall into local optimization and miss better resources. On the premise of obtaining all aspects of information, it can scientifically and effectively generate the optimal resource scheme.

However, the decision-making elements in the actual MSAR are far more complex than those considered in this paper. This paper only makes a preliminary study on the optimization of resource selection. In order to better apply it to practice, there are still many problems to be solved and studied. On the one hand, in the actual situation, the knowledge, experience and preference of decision-makers are very important. In the subsequent research, we can consider adding the preference of decision-makers to realize the combination of man and machine in the solution process of intelligent optimization algorithm, so as to realize a more reasonable solution idea. On the other hand, this paper only uses the ant colony algorithm based on the response threshold model to solve the model. In the subsequent research, it is considered to combine the response threshold model with other algorithms to carry out comparative research.

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