Recent Advances in Maritime Security Risk Detection and Rescue

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Abstract. With the continuous deepening of human exploration and utilization of marine resources, activities such as maritime trade, sea transportation, and scientific research have been increasing. However, the uncertainty of marine climate and surface environments has led to frequent maritime accidents. It is particularly important to ensure the safety of people and ships. As a result, the maritime security risk detection and rescue (MSRDR) problem, with the objectives of minimizing search and rescue time and resource consumption, has gained widespread attention. This study provides a comprehensive summary of the current state of related research, elaborating on research outcomes related to search and rescue models and path planning algorithms. Finally, it points out potential future research directions. To this end, we first present the general definition of MSRDR, followed by an introduction to two different search and rescue models: the single-center search and rescue model and the multi-center search and rescue model. Subsequently, we introduce four approaches to solving this problem, including exact methods, heuristic methods, metaheuristic methods, and reinforcement learning methods. Additionally, we discuss several potential future directions.

Keywords: Maritime Security Risk Detection; Rescue; Path Planning; Survey.

1. Introduction

Since the beginning of the 21st century, with the rapid development of international trade, transportation methods have diversified, including land, air, and sea transport, which have become the primary means of foreign trade cooperation and international exchange. Due to its advantages in stability, cost, and capacity, along with the promotion of the "Belt and Road" initiative, maritime transport has become increasingly important in international trade.

Currently, maritime platforms encompass a variety of types, including cargo shipping platforms, exploration platforms, manned platforms, and military platforms. The application scope of maritime vessels has expanded from trade and passenger transport to various industries, including scientific research, exploration, surveying, and national defense. The importance of maritime platforms is continuously increasing, and their application scenarios are becoming more widespread.

However, due to harsh marine climates, the unpredictability and suddenness of the maritime environment, and the complexity of regional economic conditions, accidents involving cargo ships, passenger vessels, oil platforms, and other maritime transportation and operational platforms occur frequently. These accidents result in significant loss of life, direct or indirect economic losses, and even damage to regional marine environments (for example, a collision involving an oil tanker can lead to the leakage of hundreds of tons of oil). Therefore, maritime search and rescue operations in response to such emergencies are receiving increasing attention from maritime authorities worldwide.

According to the European Maritime Safety Agency (EMSA), the 2024 Annual Overview of Maritime Casualties and Other Accidents reported that from 2014 to 2023, a total of 26,595 accidents occurred, with 2,896 vessels involved in maritime casualties and other incidents in 2023 alone.

To respond rapidly to search and rescue activities, various countries have organized corresponding rescue forces. With technological advancements, maritime search and rescue tools have evolved from helicopters and ships to multi-type unmanned aerial vehicles (UAVs) and amphibious aircraft, which are cost-effective, time-efficient, and have high safety standards. The scope of search and rescue has also expanded from coastal areas to more distant regions.

The method of search and rescue has gradually shifted from using single vessels or UAVs for rescue operations to a collaborative approach, where appropriate resource combinations and various resources work closely together. This change has eliminated the previous situation where search and rescue resources acted independently without unified coordination, fully leveraging the advantages of different resource types, thereby enabling multi-type combinations to handle more complex rescue tasks.

In the practical maritime search and rescue process, multiple constraints such as marine environmental factors, resource types, rescue target characteristics, and time limitations affect the search time for targets and the allocation of available resources. Multi-resource allocation and path planning further increase the complexity of the problem, expanding the algorithm's search space. Therefore, it is necessary to design efficient and reliable algorithms to solve maritime search and rescue problems.

In the field of maritime search and rescue, both domestic and international researchers have conducted extensive studies on related issues such as trajectory prediction, resource allocation, center location, resource collaboration, and multi-center coordination. With the increasing complexity of search and rescue scenarios, research on these problems has also grown significantly. Wu et al. [1] proposed a framework for the path planning of maritime search and rescue vessels, which addresses the search and rescue problem through three processes: prediction of the drift trajectory of the overboard person, establishment of a multi-area search model, and implementation of a traversal search. Cho et al. [2] addressed the multi-drone area coverage path planning in maritime search and rescue (SAR) coverage path planning (MSRDR) problem by proposing a two-stage planning method based on a grid-based area decomposition approach. Kyriakakis et al. [3] transformed the maritime search and rescue path planning problem into a vehicle routing problem and decomposed the search area using an approximate grid decomposition technique. Zhan et al. [4] proposed a graph-based planning model that takes into account multiple rescue centers, with each center allocating different search and rescue tasks based on the status of the grid it is responsible for. This model is designed to address medium- to long-range search and rescue operations.

Yang et al. [5] drew inspiration from the advantages of amphibious aircraft, such as long range, high speed, strong search and rescue capabilities, and the ability to land on water, and proposed a time-domain-based solution method for medium- to long-range maritime search and rescue using amphibious aircraft. Li et al. [6] proposed a solution method that optimizes the overall layout of charging station locations and drones. Ma et al. [7] focused on proactive warning and prediction, forecasting potential emergencies at rescue points, and establishing a model for the allocation of search and rescue resources. Due to the similarity of the problem objectives, Yao et al. [8] transformed the maritime search and rescue path planning problem into a factory robot path planning problem. Sun et al. [9] studied the optimal allocation strategy of maritime search and rescue resources, such as vessels and aircraft, along coastal islands under navigation constraints. Karatas [10] focused on the location and allocation of search and rescue resources, considering factors such as resource types, demand uncertainty, resource coordination, and resource depreciation, and proposed an overall solution approach.

Through an analysis of existing research, it has been found that the difficulty of solving search and rescue algorithms is influenced by resource constraints and environmental constraints, and is impacted by the type and quantity of rescue resources. For example, multi-resource search and rescue

problems are more difficult to solve than single-resource problems, and multi-center, multi-type resource collaborative rescue problems are even more complex than the former two. This is because, in multi-center collaborative rescue problems, it is necessary to simultaneously consider center location, resource diversity, and the complexity of constraints.

Therefore, compared to traditional search and rescue methods that rely on a single resource, the multi-center, multi-resource collaborative maritime search and rescue problem involves more constraints and a more complex solution process. This type of problem is NP-hard, posing higher demands on the design of solution algorithms.

Currently, the solution algorithms for search and rescue problems generally include heuristic methods, metaheuristic methods, and reinforcement learning approaches. Cho et al. [2] proposed a random search heuristic method to optimize the coverage path planning problem in maritime search and rescue operations. Karatas [10] considered various constraints in the rescue process and developed a dynamic multi-objective mixed integer linear programming model. Kyriakakis et al. [3] introduced a parallel weighted greedy random adaptive search algorithm with variable neighborhood descent (GRASP-VND), which optimizes the target search and local optimization problems separately.

Heuristic algorithms can certainly guarantee the optimal solution under certain assumptions. However, due to the typically exponential time complexity of heuristic algorithms, they are often unsuitable for large-scale planning problems. Metaheuristic algorithms, such as genetic algorithms, ant colony algorithms, particle swarm algorithms, and bee colony algorithms, can solve large-scale planning problems while obtaining relatively good results. These methods are widely used in solving maritime search and rescue problems.

Li et al. [6] applied an improved genetic algorithm to solve the problem. Yi [11] proposed an optimal path planning method for maritime unmanned surface vehicles using ant colony algorithms. Yu et al. [12] proposed a path planning method based on ant colony algorithms to solve the maritime search and rescue problem in the Northwest Passage.

Li et al. [13] attempted to combine multi-chromosome genetic algorithms with K-means objective clustering methods to optimize the target classification and trajectory planning process. Ma et al. [7] used an elitism-preserving genetic algorithm (EGA) to optimize the emergency resource allocation strategy involved in maritime search and rescue. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is also an effective method for solving this problem [14].

In addition, reinforcement learning algorithms have also been applied to solve this problem. Theile et al. [15] trained the drone control decision-making process using a Double Deep Q-Network (DDQN). During the coverage search phase, Wu et al. [1] constructed a Markov Decision Process (MDP) model for the path planning problem and solved it using the Deep Q-Network (DQN) based deep reinforcement learning (RL) method.

Zhan et al. [4] enhanced the effectiveness of genetic algorithms in solving complex optimization problems by introducing reinforcement learning methods during the population initialization phase and preserving the elite population.

Although reinforcement learning holds great potential for solving complex optimization problems, its challenges cannot be ignored. As the complexity of the planning problem increases, both the number of iterations and solution time also increase. Therefore, when applying reinforcement learning methods to solve problems, it is essential to consider the training costs and the generalization ability of the solution model [17].

The remainder of this survey is organized as follows. Section II introduces the general definition of MSRDR and presents two different rescue models. Section III provides a comprehensive survey of various solution methods. Section IV outlines future development directions. Section V summarize the study.

2. Maritime Search and Rescue Coverage Path Planning Problem

In this section, we first provide the general definition of MSRDR and model the problem in two different ways. We then further introduce these two distinct rescue models.

2.1 General Definition

The MSRDR involves developing a targeted rescue General Definitionplan based on different types of accidents and search and rescue resources. This plan includes selecting the rescue centers, determining the order of rescue targets, choosing rescue resources, and assigning execution times for each resource. The goal is to minimize the rescue time and maximize resource utilization, while meeting the constraints of the available rescue resources. Maritime search and rescue are a complex process, during which the following constraints need to be met:

(1) Search Area Full Coverage Constraint: This is a basic condition. During the rescue operation, depending on the search area, the rescue department divides the area into equally sized grids and conducts the search according to these grids.

(2) Rescue Target Sequence Coupling Constraint: Rather than restricting the specific search times of rescue targets, this constraint limits the relative execution sequence between rescue targets. It can be categorized into four types: multi-resource simultaneous rescue, precedence rescue, subsequence rescue, and single-resource inability to respond. This can be accurately described using a directed acyclic graph. Ignoring this constraint may result in many invalid solutions. Methods such as layered calculation of rescue targets, strongly connected component elimination, and associated rescue targets can be used to handle this constraint.

(3) Rescue Resource Constraints: The selection of rescue resources must align with the number of resources that can be mobilized. The number of a specific type of resource assigned to perform a rescue task cannot exceed its limit.

(4) Maximum Range Constraint: Due to energy consumption during the rescue process and the limited **energy** capacity of rescue resources, some rescue scenarios require consideration of return requirements. While performing tasks, rescue resources also need to account for the waiting time of the targets. Metrics such as fuel consumption, travel distance, travel time, and the maximum number of rescue targets are typically used for calculations.

(5) Rescue Time Constraint: In maritime search and rescue, the priority sequence of rescue targets differs**,** so the order of rescue also varies. Under the premise of meeting the urgency of the targets, the rescue task needs to be completed within a specified time, adhering to the time constraints of the rescue operation.

(6) Rescue Resource Capability Constraint: Rescue resources must possess the corresponding capabilities to execute the rescue task. For example, in an unmanned aerial vehicle (UAV) maritime rescue mission, when the UAV needs to carry a certain weight of rescue supplies to the target, the UAV's payload capacity must be considered. Capability can be assessed using a 0-1 variable for a simple judgment or further modeled with parameters like functional radius and execution probability.

2.2 Model

In recent years, there has been an increasing amount of research on MSRDR. To provide a clear understanding of the existing studies on MSRDR, we have surveyed the relevant literature and summarized two types of maritime search and rescue models: the single-center rescue model and the multi-center rescue model.

2.2.1 Single-center Rescue Model

Single-center search and rescue is currently the primary method used in maritime search and rescue operations. The single-center rescue model involves a unified search and rescue command center that formulates rescue plans and allocates resources, while real-time information is obtained through information exchange with the rescue resources.

This model includes the following types of search and rescue methods:

Multi-resource collaborative search and rescue: The resource types include ships, search and rescue helicopters, unmanned aerial vehicles (UAVs), etc. Aerial search forces have a wide search range, high effectiveness, and strong positioning capabilities, while maritime search forces have large capacity and can carry abundant rescue supplies. This method can leverage the advantages of different types of resources to achieve optimal search results for the accident area.

Based on the initiator of the collaborative search and rescue task, there are three main scenarios: aircraft-guided ships, ships-guided aircraft, and collaborative search by rescue resources. Karatas [10] conducted research on the collaborative search and rescue problem between ships and rescue helicopters and proposed a dynamic multi-objective mixed-integer linear programming model for optimizing the position and configuration of SAR ships and helicopters. The goal of the model is to minimize the rescue time by optimally allocating resources. The model assumes a given number of rescue helicopters and ships, which travel to the rescue area at constant speeds.

Multi-drone collaborative search and rescue: This method is mainly divided into two types. One is when drones independently complete search and rescue tasks. In this mode, different UAVs provide the target search information to the command center, which then analyzes and processes the data to gain accurate target information and deploy the appropriate rescue resources.

The second type involves multiple drones conducting joint search and rescue for a single target. In this mode, two or more UAVs in adjacent areas are combined, and through communication links between the drones, they collaborate to discover and guide the search for the target.

In this model, the maritime path planning problem is described as a given number of rescue UAVs that travel from the rescue center to the task area at a constant speed while performing the search and rescue mission. During this process, each UAV performs multiple tasks, provided that the UAV's battery life can ensure its return to the rescue center. Therefore, when a UAV cannot return to the center due to the next task, it will abandon further tasks and directly return to the rescue center. The objective of this model is to minimize the total rescue time.

2.2.2 Multi-center Rescue Model

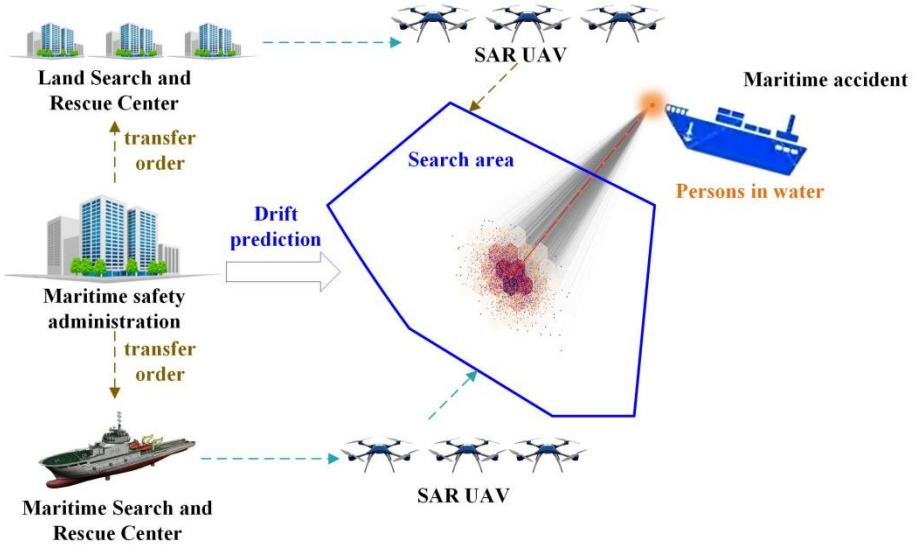


Fig 1. Maritime MSRDR Concept [4]

With the continuous enrichment and development of emergency search and rescue resources and strategies, the coordination of resources from different rescue centers has become a feasible approach and is essential to maximize the effectiveness of each center in managing its respective areas. As shown in Figure 1, multiple centers collaborate on search and rescue operations based on reported accident locations, with each center deploying different combinations of resources based on the actual circumstances of the rescue targets to carry out search and rescue tasks.

Currently, there is limited research on multi-center rescue models. The only notable study is by Zhan et al. [4], who conducted problem description and rescue model design for maritime search and rescue path planning. They established a mixed-integer programming model for multiple rescue centers to minimize the time required to complete search tasks while ensuring balanced scheduling of drones at each center.

In this model, the maritime path planning problem is described as a given number of rescue centers, with each center equipped with multiple UAVs. When performing rescue tasks, a rescue center must be selected from the set of centers, and UAVs are chosen from the selected center to travel at a specified speed to the task area. During this process, each UAV is required to perform multiple tasks, provided that its battery capacity allows it to return to the rescue center. Therefore, when a UAV cannot return to the center due to the next task, it will abandon further tasks and directly return to the rescue center. The mathematical form of the model is represented as shown below.

(1) Objective Function

$$\min \alpha_1 \cdot \left\{ \max_{k \in S} ST_k \right\} + \alpha_2 \cdot WL . \tag{1}$$

$$ST_k = \sum_{l \in U_k} \sum_{i \in T \cup \{0\}} \sum_{j \in T} t_{ij}^{kl} \cdot x_{ij}^{kl} . \tag{2}$$

$$WL = \sqrt{\frac{1}{|S|} \sum_{k \in S} \left(\sum_{l \in U_k} \sum_{j \in T} x_{0j}^{kl} - \mu \right)^2} . \tag{3}$$

$$\mu = \frac{1}{|S|} \cdot \sum_{k \in S} \sum_{l \in U_k} \sum_{j \in T} x_{0j}^{kl} . \tag{4}$$

$$\alpha_1 + \alpha_2 = 1 \cdot \tag{5}$$

Where ST_k represents the total time spent, WL represents the difference in the number of UAVs dispatched by each rescue center, μ represents the number of UAVs dispatched averaged over the number of UAVs dispatched, and α_1, α_2 represents the value of the weights.

The optimization objective of this problem is to reduce the time to complete the search while taking into account the balanced workload of each rescue center. The objective function is represented as follows.

(2) Constraints

1. Each UAV needs to depart from the rescue center.

$$\sum_{j \in T} x_{0j}^{kl} = 1, \forall k \in S, l \in U_k . \tag{6}$$

2. Each UAV needs to return to the rescue center from which it departed.

$$\sum_{i \in T} x_{i(|T|+1)}^{kl} = 1, \forall k \in S, l \in U_k . \tag{7}$$

3. UAV detection should ensure that the battery has sufficient power.

$$\sum_{j \in T} d_{0j} \cdot e_l \cdot x_{0j}^{kl} + \sum_{i \in T} \sum_{j \in T} d_{ij} \cdot e_l \cdot x_{ij}^{kl} \le E_l, \forall k \in S, l \in U_k . \tag{8}$$

$$\sum_{i \in T} \sum_{j \in T} d_{ij} \cdot e_l \cdot x_{ij}^{kl} + \sum_{i \in T} d_{i(|T|+1)} \cdot e_l \cdot x_{i(|T|+1)}^{kl} \le E_l, \forall k \in S, l \in U_k . \tag{9}$$

4. Each task is executed at most once.

$$\sum_{k \in S} \sum_{l \in U_k} y_j^{kl} \le 1, \forall j \in T . \tag{10}$$

5. All task areas need to be detected.

$$\sum_{k \in S} \sum_{l \in U_k} \sum_{j \in T} y_j^{kl} = |T| . \tag{11}$$

6. Each task needs to satisfy the equilibrium relationships of the graph structure.

$$\sum_{i \in T} x_{ij}^{kl} = y_j^{kl}, \forall k \in S, l \in U_k . \tag{12}$$

$$\sum_{i \in T \cup \{0\}} x_{ij}^{kl} = \sum_{j' \in T \cup \{|T|+1\}} x_{jj'}^{kl}, \forall k \in S, l \in U_k . \tag{13}$$

7. The range of values that decision variables can take.

$$x_{ij}^{kl} \in \{0,1\} . \tag{14}$$

$$y_{j}^{kl} \in \{0,1\} . \tag{15}$$

3. Research on Solution Algorithm

To clearly present the latest technological advancements in MSRDR, we categorized the survey literature according to different solution methods: exact methods, heuristic methods, metaheuristic methods, and reinforcement learning methods.

3.1 Exact Methods

Exact solution methods refer to mathematical or algorithmic strategies that guarantee finding the optimal solution to a problem within a finite amount of time. These methods are typically suitable for problems with smaller scales or special structures, but they may be limited in complex or large-scale problems due to their high computational complexity.

Cho et al. [2] established a MILP model for the path planning problem in maritime search and rescue, drawing inspiration from vehicle routing problem-solving approaches. The model is built with constraints based on regional characteristics and UAV capabilities, aiming to minimize the total completion time of the coverage search area as the objective function.

Considering the optimization of multi-rescue resource combinations, Karatas [10] optimized the configuration and location of rescue ships and helicopters to improve the effectiveness of search and rescue algorithms. In this process, a multi-objective problem is constructed by considering the response times of ships and helicopters, annual operating costs, and the total budget of the rescue process. At the same time, constraints such as demand uncertainty and resource variations are incorporated. Using a non-preemptive multi-objective optimization method, the deviation of each optimization objective from the normal value is adjusted, enabling effective resource allocation and assisting decision-makers in the planning of rescue base locations and the management of rescue resources.

3.2 Heuristic Methods

Due to the long computation time of exact algorithms for large-scale problems and their poor adaptability to dynamic environments, heuristic methods are incorporated for approximate solutions. Regarding path planning for similar types of UAVs, Kyriakakis et al. [3] transformed the UAV search and rescue problem into a vehicle routing problem. They employed a grid-based cell decomposition method, discretizing the search area into a set of squares, regular cells. When UAVs perform rescue tasks in the central region of the area, the grid area can be fully searched by limiting the size of the cells.

Additionally, for the capacity-constrained UAV path problem, the GRASP-VND algorithm was proposed. This algorithm addresses parallel multithreading and variable neighborhood search approaches. By using three strategies—multi-value return, best return, and random return—a multi-threaded optimization strategy is constructed. The main thread is responsible for generating new solutions, and thread communication is used to coordinate the work threads. The work threads primarily focus on the local search process, while the variable neighborhood search strategy is employed to generate optimal solutions, avoiding local optima.

3.3 Metaheuristic Methods

Metaheuristic methods are higher-level search algorithms that, compared to heuristic methods, offer higher solution efficiency and can provide better solutions. They also have strong advantages in solving multi-objective optimization problems. According to literature analysis, most of the solution algorithms for maritime search and rescue problems (MSRDR) incorporate metaheuristic methods.

Several evolutionary algorithms are widely used in MSRDR due to their simplicity, ease of implementation, and efficiency.

Inspired by the successful application of evolutionary algorithms in scheduling, Li et al. [13] proposed a combined genetic algorithm and K-means clustering method for MSRDR. This algorithm clusters target locations and encodes the clustering results as the initial chromosome population for the genetic algorithm. They introduced a multi-chromosome genetic evolution framework, optimized the cluster centers based on the K-means function, and generated the optimal solution by combining crossover and mutation strategies. Ma et al. [7], focusing on proactive warning and resource planning, proposed an elitism-preserving genetic algorithm to determine the optimal emergency resource allocation scheme. By establishing a multi-objective optimization model based on the cost of emergency resources, the response time of each rescue base, and the safety index of accident hotspots, they used a long-short term memory model and K-means clustering model, ultimately applying a genetic algorithm with elitism strategy for optimization to generate the best resource allocation plan. Li et al. [6] addressed large-scale area search problems using a genetic algorithm to solve the layout requirements of multi-UAV search and rescue and charging stations. This optimized UAV operation trajectories and charging station layouts to minimize total completion time and time within key area boundaries.

Ma et al. [14] proposed an improved NSGA-II algorithm based on multi-task optimization, addressing the complex climatic conditions at sea. To accommodate medium- to long-range search and rescue scenarios, Yang et al. [5] studied the rescue path planning problem for amphibious aircraft and rescue boats. They proposed a K-means-based clustering method for rescue targets and a GA*-based path optimization approach. In the context of actual maritime environment safety, Yu et al. [12] addressed the lack of a systematic approach to Arctic maritime search and rescue path planning in China. They constructed a maritime threat field for the Northwest Passage and used generalized network analysis to determine indicator weights, employing an ant colony algorithm to plan the search and rescue path. Yi [11] applied an ant colony algorithm-based Dijkstra method to find the global optimal solution for the shortest path under multiple constraints in maritime search and rescue.

Additionally, to accommodate navigation constraints or long-distance search and rescue operations, Sun et al. [9] transformed the optimization of maritime search and rescue resource allocation into a discrete location optimization problem. They explored how to determine the optimal deployment locations for rescue resources using an enhanced particle swarm algorithm under different numbers of ships and aircraft.

3.4 Reinforcement Learning Methods

Due to the ability of machine learning to improve the quality of solutions through data training, it holds significant potential in combinatorial optimization problems [16]. This approach can be applied in various environments, capable of responding to complex objectives and constraints. Currently, research on this method is limited, with most studies focusing on search and rescue tasks in specific scenarios.

In the scenario of search and rescue in no-fly zones, Theile et al. [15] considered key factors such as UAV energy consumption and target coverage rate, using end-to-end reinforcement learning to train decision strategies for selecting UAV takeoff and landing locations. Wu et al. [1] aimed to improve the survival probability of individuals in the water and proposed a multi-target maritime search and rescue vessel path planning framework. They developed a sea drift trajectory prediction model based on a random particle swarm algorithm and used reinforcement learning to train navigation path decision-making, maximizing the coverage of the search area and the success rate of target rescue within the effective time.

To further enhance rescue response efficiency, Zhan et al. [4] proposed a genetic algorithm based on reinforcement learning. By training the resource allocation strategy of rescue centers, they achieved joint search and rescue with multiple centers and resources, significantly reducing rescue

time. This research designed an elite depot strategy. The pseudo-code of strategy is shown in Algorithm 1.

Algorithm 1: Evaluate Elite Depot

Input: $global_best, depot$

Output: $global_best, depot$

```
1  fit ← Calculate the average fitness function value for depot;
2  If fit < global_best then
3      P ← depot ;
4  End If
5  depot = [ ]
6  Return: global_best, depot
```

4. Research on Solution Algorithm

4.1 Address More Complex Task Scenarios

Current research typically focuses on relatively fixed and simple scenarios, which still differ significantly from the situations encountered in practical applications. In future research, it is crucial for researchers to focus on more complex scenarios. Large-scale search and rescue tasks imply vast search spaces, which increases the difficulty of algorithmic solutions. Search and rescue problems in uncertain environments also pose a severe challenge. Algorithms must be sufficiently robust to minimize the impact of unexpected situations on existing solutions.

4.2 Rapid Solution Generation

Currently, most algorithms, apart from heuristic methods and reinforcement learning, tend to have much longer solution times. This is often unacceptable for many practical business systems. Future research should focus more on real-world scenarios, ensuring that models and algorithms can be applied in actual maritime search and rescue systems. However, there is still a long way to go, as the assumptions in current models are often too stringent. Relaxing these model constraints will also require higher efficiency in solution generation.

5. Conclusion

In this survey, we have conducted an in-depth discussion of the current research progress in MARSPP. The focus of this study is on problem models and solution algorithms. Detailed introductions are provided for both single-center and multi-center rescue models. Subsequently, exact solution methods, approximate solution methods, and reinforcement learning approaches are described. Additionally, we propose two potential future research directions. We believe that future studies on MSRDR will be increasingly advanced in theory and valuable in practice.

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