A decision support method for design and operationalization of search and rescue in maritime emergency

Xiong, Weitao; van Gelder, P. H.A.J.M.; Yang, Kewei

DOI
10.1016/j.oceaneng.2020.107399

Publication date
2020

Document Version
Final published version

Published in
Ocean Engineering

Citation (APA)
Xiong, W., van Gelder, P. H. A. J. M., & Yang, K. (2020). A decision support method for design and operationalization of search and rescue in maritime emergency. Ocean Engineering, 207, [107399]. https://doi.org/10.1016/j.oceaneng.2020.107399

Important note
To cite this publication, please use the final published version (if applicable). Please check the document version above.

Copyright
Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy
Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.
A decision support method for design and operationalization of search and rescue in maritime emergency

Weitao Xiong, P.H.A.J.M. van Gelder, Kewei Yang

College of Systems Engineering, National University of Defense Technology (NUDT), Changsha, China
Faculty of Technology, Policy and Management, Safety and Security Science Group (S3G), Delft University of Technology, Delft, the Netherlands

ARTICLE INFO

Keywords:
Search and rescue
Decision support
Multi-objective optimization
Differential evolution
Maritime emergency response

ABSTRACT

Design and operationalization for Search and Rescue (SAR) activities are unstructured and complex multi-criteria decision-making problems, especially for maritime emergency scenario. There is a lack of decision support methods based on intelligent algorithms to shorten the response time and to reduce the loss of life and property. The primary purpose of this paper is to develop a three-stage decision support method to optimize the type and number of resources when making SAR schemes so as to formulate emergency response more efficiently and effectively. First, the main influential factors are identified in Stage 1, including the particulars of environmental indices, search objects and SAR resources. Next, in Stage 2, important variables are defined for generating probability distribution maps, identifying the search areas, and evaluating the objective function in Stage 3. Two intelligent algorithms, the Differential Evolution (DE) and Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), are used to find appropriate SAR schemes and help resources scheduling. Finally, the feasibility and validity of the model are verified by a ship collision example. From the simulation of the SAR task assignment and decision preference analysis, the proposed method can be used for further improvement of SAR design and operationalization.

1. Introduction

Search and Rescue (SAR) in maritime emergencies may involve maritime craft, aircrafts wreckage, and lost or missing persons, such as downed aircrews, fishermen, etc. It comprises the search for and provision of aid to persons who are in danger of loss of life (Abi-Zeid et al., 2011). The Maritime SAR Center located in the Ministry of Transport of China and several sub-centers manned by local Maritime Safety Administrations are responsible for providing SAR service. Moreover, as volunteers, thousands of non-government aid participate in SAR in maritime emergencies every year. In China, there are many maritime SAR cases every month where tens of lives are lost (Ministry of Transport, 2019).

When a maritime emergency occurs, as shown in Fig. 1, SAR operations need to be planned, coordinated, controlled and commanded in response to emergency. From the perspective of search planners, the main challenge is how to provide adequate support to make emergency response more efficiently. It is a big challenge for decision makers to assign search tasks to multiple professional sub-centers and make timely decisions about SAR resources scheduling in situations where lives are at risk. Moreover, search areas must be determined appropriately to ensure that each area is covered adequately, which depends on contextual factors, such as the locations, the resources limitation as well as the number of search objects. The maritime environment also influences the SAR efficiency, which means that some factors such as waves, wind and currents should be taken into account.

The number of deaths in an emergency is expected to be minimized while the maritime environment is complex and the number and types of resources are limited. So the question of how to dispatch SAR resources in an efficient and safe way plays an important role in this research. The particulars and performance of SAR resources are essential constraints for SAR operation, such as the safety and capacity constraints. In addition, the environmental uncertainties make a difference on the SAR operation (Xue et al., 2019a). All these constraints and uncertainties make the design and operationalization of SAR a non-linear decision-making problem with limited resources. Therefore, further research into designing a search plan and optimization for SAR operation, including determining search areas, SAR resources scheduling, and decision-making algorithms is urgently needed in order to improve the SAR capability and to reduce the loss of life in maritime emergencies (Ai...
et al., 2019).

There are many studies for emergency response to maritime accidents especially using decision-making method, such as nuclear leak (Gomes et al., 2014), and ship flooding crisis (Jasionowski, 2011). Abi-Zeid and Frost (2005) presented SARPlan to assist the Canadian Forces in searching for missing aircraft, using search theory. Decision tree was used to analyze the ship accident in Turkish search and rescue area (Erol and Başar, 2015). In China, in order to mitigate the ship-bridge collision risk, some studies proposed a fuzzy logic based approach for ship-bridge collision alert system, which can be implemented in the decision support system for improving the shipping handling (Wu et al., 2019), and Wang et al. (2019) took a resilience-modulated risk model to the analysis of the Eastern Star accident and improved the system capability of emergency response. In the search group on Arctic marine technology and safety in Aalto University, the risk of oil spills in winter navigation in the Gulf of Finland was analyzed (Banda and Osiris, 2017), and Lu et al. (2019) proposed a Bayesian Network model to assess and prioritize actions to control the risk of operations. Moreover, other studies focused on the development of tools for safety and risk-informed decision-making for supporting the implementation of safety management systems in the context of maritime traffic (Banda and Goerlandt, 2018).

Note that there are two main difficulties that need to be overcome in the theory and application development. First, in the design and operationalization of SAR, the previous literature has widely agreed that this decision is driven by the task characteristics, SAR resources, risks and environment (Akbari et al., 2018). However, how to coordinate so many factors in a SAR operation and develop the Service-Oriented Architecture (SOA) based search planning decision support tools need further research. Second, scientific research into search theory itself and the resulting development are looking for being more closely coupled with their application, such as in the field of SAR crews training (Plant and Stanton, 2016) and how the basic principles of SAR are applied to forecasting the drift trajectory and search area (Wu et al., 2018b).

When solving SAR planning problems, many search planning decision support systems (DSS) were developed (Vidan et al., 2016). The U.S Coast Guard’s Search and Rescue Optimal Planning System (SAROPS) started in October 2003, and the version 1.0 was deployed in early 2007 (Kratzke et al., 2010), which is the successor to the Computer-Assisted Search Planning (CASP) System (Richardson and Discenza, 1980). As a new generation DSS, the Advanced Search Planning Tool (ASPT) (Abi-Zeid et al., 2019), is being developed by the Canadian Coast Guard in order to replace the current Canadian Search and Rescue Program (CANSARP) (Guard, 1993). And there is a matrix summary of classical search planning tools in the work of Frost and Stone (2001). Furthermore, a software tool, namely SARGIS (Guoxiang and Maofeng, 2010) was designed to provide supporting databases, application modules and graphical user interface for SAR. In China, the State Oceanic Administration organized the North China Sea Forecasting Center, the Eastern China Sea Forecasting Center, the South China Sea Forecasting Center, the National Marine Environment Forecasting Center, the National Marine Data and Information Service, and researchers in Shandong University of Science and Technology to develop the National Maritime Search and Rescue Support System (NMSARSS). The system integrates multiple modules including drift prediction, marine environmental forecasting visualization and collaborative service, which greatly reduces the emergency response time and improves the prediction accuracy of maritime SAR (Gao Song, 2019).

The evaluation and selection of SAR resources are more dependent on empirical judgment rather than intelligent algorithms at present, and it is difficult to improve the reliability and efficiency of decision-making. Therefore, a better method should be further developed to overcome this drawback, creating a clear multi-objective decision support method to optimize the design and operationalization of SAR schemes.

To address these problems, we have developed a three-stage decision support model to help the decision maker find an optimal SAR scheme after maritime emergency happened. In this paper, the design and operationalization of SAR is modeled as a Multi-Objective Optimization Problem (MOOP) by considering the success rate of SAR and the total cost. Which part we investigate in the SAR planning problem is to answer how many and which types of SAR resources should be implemented in a maritime emergency response. And the NSGA-II is used to find the Pareto solutions set for optimizing the numbers and types of SAR resources. In order to obtain the compromise solution for final decision-making, the Technique for Order of Preference By Similarity to Ideal Solution (TOPSIS) can be applicable to such MOOP after generating the Pareto solutions set (Hwang and Yoon, 1981). As a classical multi-attribute decision-making method, the TOPSIS method is widely used to select the compromise solution owing to its concept of choosing the alternative by considering the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal position (Wu et al., 2018a). This paper provides the following contributions: (1) A three-stage decision support method is developed for SAR resources scheduling and tasks assignment; (2) Two intelligent algorithms were introduced to find the optimal solutions about the required types and number of the SAR resources, considering success rate and total costs. (3) How to balance different objectives when dispatching SAR resources under different decision preference is
The remaining sections of this paper are organized as follows. Section 2 formulates the SAR decision support model including integrating influencing factors, describing important variables, and designing the algorithm. Moreover, the drift prediction and the method of determining search area are introduced in Section 2.2 and 2.3. In Section 2.4, the single objective optimization model with the DE algorithm is outlined first. Based on single objective model, the 2.4.2 part extends it to a multi-objective model, considering risk costs and direct costs. An illustrative example about a ship collision and corresponding results are provided in Section 3 to verify the decision support method. A drift prediction and search area identification are obtained based on NMSARSS. Section 4 makes a comparison of SAR schemes by search effort analysis and tasks assignment simulation. Decision preference is also discussed in Section 4. Section 5 concludes the paper with a summary of the results. We also introduce future work directions in this part.
Fig. 3. The maritime environmental parameters.
2. Methodology: A SAR decision support model

2.1. Framework of the proposed model

As introduced and discussed in Section 1, the emergency response to maritime SAR incidents should be time sensitive and SAR resources should be organized effectively and intelligently. In this section, a three-stage decision support model is developed to meet these requirements. The Stage 1 combines parameters of the search object, environment and SAR resources for search planner to predict drift trajectory systematically, which is discussed in Section 2.2. Next, the SAR principles and variables are analyzed in Stage 2. Important variables, such as the probability of containment (POC), probability of detection (POD), and the probability of survival, are described in this part to demonstrate the process of generating a probability distribution map and determining search areas. Moreover, these variables are the basis of formulating objective functions in Stage 3. In Stage 3, there are two main intelligent algorithms introduced. One is the DE for a single objective model, concerning about the success rate only. The other is the NSGA-II for a multi-objective model, taking the objective function of total cost into account to evaluate the loss of property. The feasible SAR schemes are obtained by DE and NSGA-II. Moreover, the TOPSIS is applied to select compromise solution from the Pareto front. At the end of Stage 3, the final decision is made based on the comparison of SAR schemes and decision preferences. The framework of the proposed decision support method is shown in Fig. 2.

2.2. Stage 1: integration of influencing factors

2.2.1. The parameters of environment and search objects

The SAR resources scheduling and search tasks assignment are related to the environmental factors. The NMSARSS system integrates the influencing factors from its maritime environment. The dynamic data of wave height, wind, current, and temperature in a specified location can be provided and visualized quickly to predict the drifting routes. As shown in Fig. 3, if we want to forecast the maritime environment and make a drift prediction for a search object at a given start location (Longitude: 120°68'E, Latitude: 35°83'N), we can download these environmental data and see how they will change over time.

In Fig. 4a, the scenario with date, location, and types of search objects have been set for the drifting prediction. The setting of wind field coefficient (0.08, 0.05, 0.02, 0.015, 0.01) depends on the types of objects (such as a low power fishing boat, life raft, life ring-upright, life vest-upright, or life vest-lying). The maximum forecasting duration can be set 72 h. A drift prediction example in 24 h is visualized in Fig. 4b. The yellow arrows represent the sea current and the blue “F” marks the wind direction. Each set of particle’s positions in time represents a search object’s likely trajectory (Breivik and Allen, 2008). The Monte Carlo based stochastic drift simulation’s output, drift file containing the particles’ positions at each time step, is an input to decision support system for search planning.

2.2.2. SAR resources

The paradigm of decision result is a vector solution which includes the type and number of specific SAR resources. The paradigm can be expressed as:

\[ X = (x_1, x_2, x_3, \ldots, x_M) \]  

Where \( M \) indicates the total types of available SAR resources, and \( x_i \) is the number of SAR resource \( i \) participating in the SAR operation. If \( x_i = 0 \), it means that resource \( i \) is not used during a SAR operation.

| Notation: Parameters | Description |
|----------------------|-------------|
| \( i \)              | The serial number of SAR resources type |
| \( x_i \)            | The number of resource \( i \) participating in SAR |
| \( b_i \)            | The safe sea state levels of resource \( i \) |
| \( c_i \)            | The direct costs of resource \( i \) (euro/h) |
| \( G_i \)            | The geographic coordinate of resource \( i \) |
| \( V_i \)            | The speed of resource \( i \) (knot, mmi, h) |
| \( nc \)             | The number of particles in a grid cell |
| \( np \)             | The total number of particles |
| \( A \)              | The containment area |
| \( OA \)             | The overall area |
| \( S_{track} \)      | The track spacing |
| \( M \)              | The types of resources |
| \( N \)              | The number of people in water |
| \( W \)              | Sweep width |

2.3. Stage 2: SAR principles and variables

In order to develop a search plan and optimize the SAR resources, some basic SAR principles and variables need to be defined and analyzed. The process of considering these variables is also the preliminary work of generating a search plan, such as generating
probability distribution map and determining search area. Moreover, the definition of objective functions in Stage 3 are based on this stage.

**Notation:**
- \( dc \): The containment density
- \( dg \): The overall density
- \( r \): The density ratio
- \( T_i \): The search time of resource \( i \)
- \( Temp \): The average sea surface temperature (°C)
- \( Z \): Search effort, area effectively swept
- \( C \): Coverage (or search effort density)
- \( POC \): The probability of containment
- \( POD \): The probability of detection
- \( POS \): The probability of Success
- \( P_{\text{survival}}(t) \): The probability of survival in water as a function of time

### 2.3.1. Description of variables

#### 2.3.1.1. The probability of containment.
When completing and optimizing a SAR plan, a prior probability density distribution on the search object location, which is also named the probability of containment (POC), is the first probability map to derive. In order to calculate the POC, it is necessary to define the search area, and transform it into a probability distribution map by dividing it into several cells (Agbissoh Otote et al., 2019). As shown in Fig. 5, the possible locations of a search object in 3 h are regarded as the movement of scatter points. An initial search rectangle can be given. And the color in the cells visualized using NMSARSS indicate the gradient of the POC. Its value is decreasing from the inside out. In this section, a process of the POC calculation built-in NMSARSS is briefly introduced.

We use the map in Fig. 5 as an example. The density ratio \( r \) should be considered to calculate the POC in a grid cell. And it is determined by containment density \( (dc) \) and overall density \( (dg) \). The formula involved are as follows:

\[
dc = \frac{nc}{A} \quad (2)
\]

\[
dg = \frac{nt}{OA} \quad (3)
\]

\[
r = \frac{dc}{dg} \quad (4)
\]

where \( nc \) is the number of particles in a grid cell, \( A \) is the containment area of a grid cell, \( nt \) is the total number of particles, and \( OA \) is the overall area such as the rectangle drawn with red line in Fig. 5. Thus, the POC value of a selected search area can be calculated according to equation (5).

\[
POC_{\text{cell}} = 1 - e^{-r} \quad (5)
\]

#### 2.3.1.2. The probability of detection.
The probability of detection (POD) is a variable associated with the SAR units. Previous studies have shown that the POD can be modeled as an exponential function of coverage \( C \) (Frost, 1999a) in equation (6).

\[
POD = 1 - e^{-C_i} \quad (6)
\]

where \( C_i = \frac{W}{S_{\text{track}}} \), as defined in modern search theory, is a measure of how thoroughly an area was swept (also equals the ratio of the area effectively swept divided by the physical size of the area where sweeping was done). \( W \) is the sweep width and it has a strong relationship with the different detectors, search environment, and types of search objects. \( W \) is obtained by statistical analysis of large numbers of experimental and real data (Wu and Zhou, 2015). \( S_{\text{track}} \) is the track spacing and it depends on the search pattern and path. The linear search (Koopman, 1957) is a method for finding an element sequentially (Expanding square & Parallel glance, as shown in Fig. 6). These search patterns are suitable for a large search area which needs to be covered evenly.

![Fig. 5. The probability distribution map.](image)

![Fig. 6. Linear search pattern.](image)
2.3.1.3. The probability of survival. When evaluating a search plan for emergency, the search time of SAR resources \( T_i \) should be taken into account. Because the duration of a search plan has an impact on the probability of survival \( P_{\text{survival}}(t) \). It is necessary to determine the final search area of each SAR resource before calculating \( T_i \). The process about how to assign the overall search area to different SAR resources is explained in Section 2.3.2. If a search area \( S_i \) is swept by resource \( i \) completely, the following equation should be satisfied: 

\[
T_i = \frac{S_i}{x_i V_{\text{max}}} \quad (7)
\]

Moreover, McCormack et al. (2008) calculated the \( P_{\text{survival}}(t) \) as a function of time and ambient temperature for people immersed in water (Temperature: 0–25 °C). From his work, the survival relationship can be expressed as equation (8):

\[
P_{\text{survival}}(t) = \exp \left( -0.349t \times \exp(-0.094 \times \text{Temp}) \right), t \leq \max(T_i) \quad (8)
\]

2.3.2. Design and optimization for SAR resources

The key part of the proposed decision support method for SAR plan is to optimize the type and number of SAR resources. The decision variables of the model are the \( X \), as explained in formula (1). Next we need to design and optimize the details of search plan, including the final area assignment and SAR resources.

2.3.2.1. Task assignment for SAR resources. According to the previous description, the initial search area has been divided into several grid cells of the same size. This section introduces how to combine some of the cells and assign them to SAR resources. The goal of task assignment for SAR resources is to maximize the probability of search success (POS) which is related to the POC and POD (Abi-Zeid and Doyon, 2003). The following steps are the guidelines to determine the search area of SAR resource \( i \).

Step1: Choose the first search rectangle based on probability distribution map. The grid cell of highest POS is selected as the initial search area, and deduce the \( \text{POS}^i = \max(\text{POCell}) \times \text{PODr}_i \).

Step2: Add one row or one column along each side of the search area to generate a new rectangle. And recalculate the \( \text{POS}^i \) of the newly obtained area. Compare the value of the two search areas. If \( \text{POS}^2 \) > \( \text{POS}^1 \), the new rectangle is observed as the current search area, otherwise the rectangle from the previous step is retained. Fig. 7 shows the process briefly.

Step3: Repeat the above process until the POS no longer increases. Then the forming process is terminated and the current rectangle is assigned to the resource \( i \) as search task. In other words, the \( S_i \) in equation (7) is obtained.

When making the next task assignment, the overall area should subtract the \( S_i \). Then follow steps one to three to re-determine search area for another resource. The search areas do not overlap each other (Ai et al., 2019).

2.3.2.2. Constraint analysis. This part discusses the mathematical constraints in the proposed decision support model, instead of the constraints in search theory such as path constraints (Eagle and Yee, 1990) and simplicity constraints (Richardson and Discenza, 1980). According to the real environmental conditions and the SAR resources particulars, there are some inequality constraints for SAR operation (Guo et al., 2019). The following is a summary of four types of constraints in this model.

First, the available number of resources is limited in different organizations. For example, there may be some resources occupied in other tasks when a new emergency occurs. Therefore, SAR resources scheduling cannot be more than the total number of each type of resources, as shown in inequality (9):

\[
0 \leq x_i \leq n_i, x_i \in N, i = 1, 2, \ldots, M
\]

Second, the scale of sea state is divided into 9 levels, as shown in Appendix A. The higher the level is, the severer the maritime environment is. In order to make sure that SAR resources are working under a safe environment, there is a maximal safety level that allows them carrying out SAR tasks. So when dispatching SAR resources, the decision makers should also take the sea state into account. The maximum allowable sea state should be greater than the current sea state level:

\[
b_i \geq B, b_i \in \{0, 1, \ldots, 9\}, i = 1, 2, \ldots, M
\]

Third, different vessels have different capacity, and there is a limited capacity of a vessel. So the rescue vessels should be dispatched to accommodate more people than the expected number of people in water, as shown in inequality (11):

\[
N \leq \sum_{i=1}^{M} u_i
\]

Fourth, the search time should be smaller than the people’s longest survival time in water at Temp C:

\[
\max(T_i) < h_{\text{max}}(\text{Temp}), i = 1, 2, \ldots, M
\]

2.4. Stage 3: algorithm design and model solving

As the basic search variables and planning method can be obtained by conducting the above two stages, Stage 3 manages to design intelligent algorithms to solve the single objective and the multi-objective model for optimizing SAR resources. Two objective functions are introduced to assess the SAR schemes. The \( P_{\text{success}} \) describes the success rate of SAR operation by considering the SAR resources, \( P_{\text{survival}}(t) \), the POC, and the POD together. Another objective function is the total cost of SAR operation, including the \( C_{\text{risk}} \) and \( C_{\text{direct}} \). The costs criteria have

---

**Fig. 8.** The standard algorithmic framework of DE.
been widely used in risk analysis and decision-making (Wu et al., 2017), and here it represents the payment used for executing search tasks and the cost of life lost in maritime emergency.

First, DE is applied to solve the single objective model. Second, since adding the cost criteria, the NSGA-II is applied to find the Pareto solution for the multi-objective model. Third, the TOPSIS method is introduced to find the compromise solution of optimizing the SAR resources.

2.4.1. The single objective model

According to the decision variables paradigm (1), the scale of solution space is

$$\prod_{i=1}^{M} \left(\left[\max(x_i) - \min(x_i) + 1\right]\right) \geq 2^M \quad (13)$$

The scale of solution space increases exponentially as $M$ increases, which means the problem of optimizing number and types of SAR resources, is an NP-hard problem. As an intelligent optimization method, DE is reasonable to solve this kind of problem (Storn and Price, 1997). The standard algorithm framework is shown in Fig. 8. More details on DE are given below.

Step1: Initialize the population. According to the paradigm, we encoded the decision variables in decimal integers. The encoded form of an original individual is designed as

$$X_i(0) = (x_{i1}(0), x_{i2}(0), \ldots, x_{iM}(0)), i = 1, 2, \ldots, np$$

Where $np$ is the size of population. The number in the parenthesis indicates which generation over the whole iterative process. The upper boundary of every vector component depends on the available number of the corresponding resources.

Step2: Define the objective function $f_i$. It consists of the fitness and penalty functions. Given the constraints analysis in Section 2.3.2, we applied the penalty function to address the constraint. The fitness function is designed as $1 - P_{\text{success}}$. So that the lower a fitness value is, the better success rate an individual has:

$$f_i = 1 - P_{\text{success}} + \sum_{l=1}^{M} \left\{ L_1 \max(B - h_l, 0) + L_2 \max(T_l - h_{\max}(\text{Temp}), 0) \right\}$$

$$P_{\text{success}} = \frac{\sum_{i=1}^{M} x_i \cdot \text{POC} \cdot \text{POD} \cdot \text{P}_{\text{success}}(f_i)}{\sum_{i=1}^{M} x_i} \quad (15)$$

The objective function derived from the success rate is defined and calculated by equations (14) and (15), which means not only searching out the people in water but also making sure they are alive. The $L_1, L_2, L_3$ are three large numbers which represent penalty factors when the corresponding limit is exceeded.

Step3: Mutation operation. The individuals in the g-th generation are marked as

$$X(g) = (x_{i1}(g), x_{i2}(g), \ldots, x_{iM}(g)), i = 1, 2, \ldots, np$$

We randomly choose three different individuals $X_{p1}(g), X_{p2}(g), X_{p3}(g)$ and use equation (16) to generate the mutant individual $H_i(g)$.

$$H_i(g) = X_{p1}(g) + F \cdot (X_{p2}(g) - X_{p3}(g)) \quad (16)$$

where $F$ is the scale factor that controls the influence from differential vector, recommended as 0.5 (Price et al., 2006).

Step 4: Crossover operation can enrich the diversity of population. The specific method is explained as Fig. 9 and function (17):

$$v_{ij} = \begin{cases} h_i(g), \text{rand}(0, 1) \leq cr \\ x_i(g), \text{else} \end{cases}$$

(17)

Where $cr \in [0, 1]$ indicates the crossover probability, recommended as 0.2 (Wan et al., 2018); rand(0, 1) is a random number obeying uniformly distribution between [0, 1].

Step 5: Selection and iteration. By comparing the fitness values of $X_i(g)$ and $V_i(g)$, we can pick the preferable individual as $X_i(g + 1)$. So the selection process is as follows:

$$X_i(g + 1) = \begin{cases} V_i(g) \quad \text{if } f_i(V_i(g)) < f_i(X_i(g)) \\ X_i(g) \quad \text{else} \end{cases}$$

(18)

Given the limits of iteration ($nm$), the DE operation can proceed to steps 3 again or be stopped.

2.4.2. Use of an improved multi-objective model for decision support

The total costs during SAR operation consists of the risk and direct costs. In this paper, risk costs are defined as the sum of economic loss of failing to find the search objects, multiplied by the probability of that loss occurring. We assume that $C_{\text{risk}}$ is the economic loss of failing to find search objects, multiplied by the probability of that occurring. Therefore, the total costs should be considered as redundant SAR plan. So that the lower a fitness value is, the better success rate an individual has:

$$C_{\text{risk}} = (1 - POD) \cdot N \cdot k$$

$$POD = \frac{\sum_{i=1}^{N} x_i \cdot POD_i \cdot P_{\text{success}}(f_i)}{\sum_{i=1}^{N} x_i} \quad (19)$$

In general, the mean of $POD_i$ will be improved when increasing the number of SAR resources involved. However, the direct cost will increase as well. Because allocating resources excessively results in a redundant SAR plan. Therefore, the total costs should be considered as an economic indicator to assess the loss of property.

For a SAR operation solution $X = (x_1, x_2, x_3, \ldots, x_M)$, the total costs $C_{\text{total}}$ is calculated by the above objective functions.
are defined as:
\[
f_2 = C_{\text{risk}} + C_{\text{direct}} \\
= (1 - POD) \cdot N \cdot k + \sum_{i=1}^{M} x_i c_i T_i
\]
(20)
where \(C_{\text{Direct}}\) is the total direct costs of executing a SAR operation, such as the flight costs of helicopters and shipping costs of vessels. It is defined as a sum of direct costs estimation of all SAR resources involving in a search plan.

According to the total costs equation (20) and the single objective model which is related to success rate and, we build a multi-objective optimization model, which allows the decision makers to balance success rate and total costs, and choose a satisfying solution to complete the optimization model, which is related to success rate and, we build a multi-objective genetic algorithms.

NSGA-II is an improved algorithm which overcomes the high computational complexity of NSGA and the lack of elite strategy (Srinivas and Deb, 1994). In this paper, it is used to find Pareto solutions for SAR operation. The overall process of NSGA-II can be described as Fig. 10 (Deb et al., 2000). There is no need to discuss the specific details about initializing population and genetic operation in this paper. What we concerned about is the comparison process among various solutions.

NSGA-II uses a fast non-dominated ordering mechanism to reduce the computational complexity of ordering. First, define \(\phi(X) = \sqrt{f_1(X)^2 + f_2(X)^2}\), and use \(X_i < X_j\) to denote that the solution \(X_i\) dominates the solution \(X_j\). Then, the non-dominated sorting principles are summarized below:

\(X_i < X_j\), if and only if one of the following conditions is true:

1. \(X_i\) is a feasible solution, and \(X_j\) is an unfeasible solution;
2. Both \(X_i\) and \(X_j\) are unfeasible solutions, and \(\phi(X_i) \leq \phi(X_j)\);
3. Both \(X_i\) and \(X_j\) are feasible solutions, and \(f_1(X_i) \leq f_1(X_j), f_2(X_i) \leq f_2(X_j)\).

Those solutions \(X^*\) in the 1st rank generate a Pareto front where solutions are non-dominated, which means that the algorithm cannot find a feasible solution better than \(X^*\). That is to say, feasible solutions of higher success rate and less total costs than Pareto solutions meanwhile do not exist.

2.4.3. TOPSIS method

We select the compromise solution from the Pareto Front using TOPSIS. The main steps are explained as follows:

Step 1: normalizing the decision matrix \(A = (a_{ij})_{h \times 2}\)
\[
a_{i1} = f_1(X_i^*) \\
a_{i2} = f_2(X_i^*)
\]
\[
m_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{h} a_{ij}^2}}
\]
(21)
\(i = 1, 2, ..., h; \; j = 1, 2\)

where \(h\) is the number of Pareto solutions. So the matrix \(M = (m_{ij})_{h \times 2}\) is the normalized matrix of \(A = (a_{ij})_{h \times 2}\).

Step 2: Calculating a weighted normalization decision matrix \(R = (r_{ij})_{h \times 2}\)
\[
r_{ij} = m_{ij} \times w_j
\]
(22)
where \(w_j\) is the weight value of the \(j\)-th objective.

Step 3: Define the positive and the negative ideal solutions:
\[
f^+_i = \min_{j} r_{ij} \\
f^-_i = \max_{j} r_{ij}
\]
(23)
\(i = 1, 2, ..., h; \; j = 1, 2\)

Fig. 10. The main process of NSGA-II.
Step 4: Calculating the distance between the feasible solution and $f_j^*$:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (f_j - f_j^*)^2}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (f_j - f_j^*)^2}$$

(24)

Step 5: Calculating the proximity of the feasible solution to the ideal solution:

$$D_i = \frac{D_i^- + D_i^+}{i = 1, 2, ..., n}$$

(25)

In the end, we sort $D_i$ in descending order. The solution of the maximum value of $D_i$ is the compromise solution in the Pareto solution set (Zavadskas et al., 2016).

3. An illustrative example

3.1. Description of the emergency scenario

At 01:44 a.m., on October 30, 2019, a ship collision happened (123°45'E, 37°15’N) between a fishing ship and a bulk ship whose detailed information is shown in Table 1. Eleven people were missing. The Weihai Maritime Rescue Center received the alarm and launched an emergency response at 02:28 a.m. In order to verify the validity of the proposed decision support method, this paper takes the collision event as an illustrative example to discuss how to apply this method in design and operationalization of SAR. The data of environmental factors, such as wind, current, wave and temperature can be obtained from the CNMSARSS, as shown in Fig. 11. The drift prediction of people was simulated after confirming the alarm. The blue line which starts from a green point and ends at a red one shows the main drift track within 24 h. The grey points show the possible locations of people in water. In addition, the detailed information of the drift prediction is restored every hour in Table 2. Once a maritime emergency happened, the number and types of SAR resources need to be urgently selected and optimized.

According to the detailed information of SAR resources in Table 3, there is a fishing vessel and one cargo vessel available near the place where the collision happened. Moreover, other types of resources (No.1-8) are affiliated with Maritime Safety Administration and other professional rescue organization. Hence, a feasible solution can be expressed as $X = (x_1, x_2, ..., x_{10})$.

The average sea surface temperature is 14 °C. According to the reference table in Appendix A2, the longest expected survival time is $h_{\text{max}}(14) = 6h$. Based on the environmental indices in the first 6 h and the classification in Appendix A1, we can evaluate the current sea state is B = 2nd. And the numbers of people in water is $N = 11$. In order to compute Coverage and POD, some typical SAR resources’ sweep width table are given in Appendix B (Guard, 1986). The visibility is 3–5 nautical miles. In this case, the linear search is applied in SAR operation and the track spacing $S_{\text{track}}$ is 0.1 nautical miles.

The parameters applied in this case associated with DE are depicted

| No. | Time      | Longitude   | Latitude   | Current | Wind |
|-----|-----------|-------------|------------|---------|------|
|     |           |             |            | Speed (m/s) | Angle (°) | Speed (m/s) | Angle (°) |
| 01  | 10:30:01:44 | 123°45'00"E | 37°14'58"N | 0.52    | 171.9 | 3.39    | 286.5 |
| 02  | 10:30:02:44 | 123°45'28"E | 37°13'31"N | 0.64    | 166.2 | 3.34    | 269.3 |
| 03  | 10:30:03:44 | 123°46'04"E | 37°12'43"N | 0.60    | 160.4 | 3.56    | 263.6 |
| 04  | 10:30:04:44 | 123°46'41"E | 37°11'51"N | 0.39    | 154.7 | 4.42    | 257.8 |
| 05  | 10:30:05:44 | 123°47'13"E | 37°11'28"N | 0.12    | 131.8 | 5.12    | 257.8 |
| 06  | 10:30:06:44 | 123°47'34"E | 37°11'39"N | 0.22    | 355.2 | 5.29    | 257.8 |
| 07  | 10:30:07:44 | 123°47'40"E | 37°12'27"N | 0.47    | 343.8 | 5.18    | 252.1 |
| 08  | 10:30:08:44 | 123°47'32"E | 37°13'29"N | 0.62    | 343.8 | 4.58    | 246.4 |
| 09  | 10:30:09:44 | 123°47'14"E | 37°14'43"N | 0.61    | 338.0 | 4.92    | 234.9 |
| 10  | 10:30:10:44 | 123°46'55"E | 37°15'46"N | 0.43    | 332.3 | 5.69    | 223.5 |
| 11  | 10:30:11:44 | 123°46'45"E | 37°16'24"N | 0.16    | 309.4 | 6.61    | 223.5 |
| 12  | 10:30:12:44 | 123°46'49"E | 37°16'27"N | 0.23    | 183.3 | 7.01    | 223.5 |
| 13  | 10:30:13:44 | 123°47'11"E | 37°15'55"N | 0.51    | 166.2 | 7.17    | 229.2 |
| 14  | 10:30:14:44 | 123°47'50"E | 37°15'00"N | 0.68    | 160.4 | 7.72    | 229.2 |
| 15  | 10:30:15:44 | 123°48'41"E | 37°15'37"N | 0.67    | 160.4 | 8.07    | 229.2 |
| 16  | 10:30:16:44 | 123°49'35"E | 37°13'07"N | 0.51    | 154.7 | 8.33    | 229.2 |
| 17  | 10:30:17:44 | 123°50'24"E | 37°12'45"N | 0.24    | 131.8 | 8.67    | 229.2 |
| 18  | 10:30:18:44 | 123°51'00"E | 37°13'01"N | 0.18    | 22.9 | 9.16    | 223.5 |
| 19  | 10:30:19:44 | 123°51'20"E | 37°13'51"N | 0.45    | 355.2 | 8.80    | 229.2 |
| 20  | 10:30:20:44 | 123°51'24"E | 37°15'10"N | 0.66    | 343.8 | 9.61    | 223.5 |
| 21  | 10:30:21:44 | 123°51'15"E | 37°16'42"N | 0.72    | 338.0 | 9.42    | 223.5 |
| 22  | 10:30:22:44 | 123°51'01"E | 37°18'09"N | 0.59    | 338.0 | 9.71    | 229.2 |
| 23  | 10:30:23:44 | 123°50'51"E | 37°19'12"N | 0.36    | 326.6 | 9.59    | 234.9 |
| 24  | 10:30:00:44 | 123°50'52"E | 37°19'41"N | 0.09    | 252.1 | 9.35    | 234.9 |
design and optimize the types and number of SAR resources. In this section, the search area should be assigned to the search area in order to maximize the success rate and minimize the total cost.

From the description of the emergency scenario above, the SAR resources scheduling schemes including the types and number solved by DE can be obtained in three different time intervals respectively. Other results solved by Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are treated as a comparative experiment for the single objective model. For every time interval, we run the three algorithms ten times respectively under the same parameters settings (as depicted in Table 4) and then save the best evolutionary curves data of every algorithm. The best evolutionary curve records the process of obtaining the relative minimum \( f_1 \) of 10 runs. Next, three kinds of best evolutionary curves corresponding to the three algorithms are shown in Fig. 13a, b, c under different time intervals, with the evolutionary generations as abscissa and \( f_1 \) in equation (14) as the ordinate. The number of evolutionary generations indicates the iteration in the process of running algorithms. For example, it can be seen from Fig. 13a that DE can obtain the relative minimum \( f_1 = 0.192 \) at the 73rd generation. The detailed results under different time intervals, including the compromise solutions solved by NSGA-II and TOPSIS for the multi-objective model in different intervals.

In different time intervals, the search planner decides the SAR source scheduling schemes according to the environment and available resources. A smaller \( f_1 \) indicates a higher success rate, which means the corresponding search plan is better. As can be seen from Table 5, when discussing the single objective model, the \( P_{\text{success}} \) of SAR schemes obtained by DE and PSO are significantly greater than that obtained by GA. But in [05:44–07:44], PSO cannot converge to find the optimal solution. In a same time interval, the SAR schemes obtained by DE use fewer resources to reach the same \( P_{\text{success}} \) compared with schemes obtained by PSO. It can be seen from Fig. 13a, b, c that the objective value curves based on the DE converge to an optimal solution at a fast speed. That is because the DE uses a simple mutation operation and one-to-one competitive survival strategy to reduce the complexity of a genetic operation. In summary, DE for this decision support model is robust and has strong global convergence ability.

Another significant performance variable is the probability of survival, as part of the objective function. As time goes by, the probability of survival declined, resulting in decrease of the \( P_{\text{success}} \). It warns that the search plan should be designed and operated as soon as possible, especially during the most likely survival time.

For a multi-objective model, we generate the Pareto front using NSGA-II and find the compromise solution using TOPSIS in which the

![Fig. 12. Three search probability distribution maps.](image-url)
Fig. 13. The objective value comparison (a, b, c) and the compromise solution (d, e, f).
weights of both objectives are equal. Fig. 13d, e, f show the results of multi-objective model. These solutions in the Pareto front means that the algorithm cannot figure out which search plan is better. The weights of the two objectives are set at 0.5. After generating the positive and negative solution of TOPSIS, we can find the compromise solution marked with data tips. Taking the solution from Fig. 13e as an example, the results with more information about the relationship between the success rate and the total cost are shown in Fig. 14. From Fig. 14, it could be concluded that the success rate is improved when the decision maker increases the cost of allocating SAR resources. The growth process of the success rate can be divided into three phases based on the gradient change. The decision can be made more accurately and easily, when the search planner notices that the success rate improved greatly from point A to B. However, the success rate increases inefficiently in phase I and more costs would be required in phase II if they want to obtain a same improvement as in phase II. That is why a rational decision maker will prefer to choose point B as the final SAR schemes when balancing two objectives, which is also the compromise solution obtained by TOPSIS in [03:44–05:44].

4. Discussion

The analysis and reasoning surrounding the results is covered in this section. We also make a comparison of search schemes from two aspects, including search effort and search task assignment. Moreover, the selection of the weights of the objectives to reflect the decision preference is discussed by analyzing some decision makers’ requirements.

4.1. Comparison of SAR schemes

An important thing which should be noted is that the search task assignment will influence the search efficiency. Every ship or aircraft has its own search time and search area. In order to evaluate the search efficiency of each ship, search effort is introduced in this part. The search effort is defined as the distance traversed within the area of interest. It maybe equivalently defined as the amount of time spent in the area of interest times the average speed of broom (Frost, 1999b).

\[
Z = \sum_{i=1}^{M} \alpha_i W_i V_i T_i, \tag{26}
\]

If multiple vessels and aircrafts are used simultaneously, then the effort should be multiplied by the number accordingly. To demonstrate the decision support method of optimizing SAR resources scheduling schemes, we further make a comparison of search effort between the scheme \(X_B\) obtained by DE and the compromise scheme \(X_B\) based on NSGA-II and TOPSIS in [05:44–07:44], as shown in Table 6.

According to Table 6, after adding the total costs as another objective, the search time of \(X_B\) is longer than that of \(X_A\). Obviously, the number of Beihei rescue 116 (No.3) and offshore patrol vessel (No.6) become less or zero because of its expensive direct cost, which leads the search effort of the offshore patrol vessel to decline and the task assignment for it to decrease. As a result, the other ships’ search time for people in water becomes longer. It can be seen from Table 6 that fishing ship (No.9) cannot reach the search area on time and execute the SAR task in scheme \(X_B\). That is because the search area has been assigned to other available ships which are faster and closer to the search object. The simulations of SAR schemes \(X_A\) and \(X_B\) are visualized in Fig. 15. The overall search area is fully covered and divided as several search tasks.
different weights are shown in Table 7. If the decision makers are cost-sensitive, they tend to choose a higher weight of total costs.

Table 7

| (1 − P_{succ}) weight | Total costs weight | Success rate | Total costs |
|-----------------------|-------------------|--------------|-------------|
| 0.1                   | 0.9               | 58.3%        | 10.87       |
| 0.2                   | 0.8               | 58.3%        | 10.87       |
| 0.3                   | 0.7               | 58.3%        | 10.87       |
| 0.4                   | 0.6               | 58.3%        | 10.87       |
| 0.5                   | 0.5               | 63.3%        | 12.10       |
| 0.6                   | 0.4               | 67.6%        | 13.59       |
| 0.7                   | 0.3               | 67.6%        | 13.59       |
| 0.8                   | 0.2               | 67.6%        | 13.59       |
| 0.9                   | 0.1               | 67.6%        | 13.59       |

Fig. 15. Simulations of search task assignment.

4.2. Decision preference

Different decision makers may have different preferences to the two objectives (Xue et al., 2019b). Thus, we next set out to use different weights for the success rate and total costs in a Pareto solution set. The objective function values of compromise scheme in [03:44–05:44] under different weights are shown in Table 7. If the decision makers are preferred to obtain a higher success rate, they can set the weight of the total costs objective lower. In contrast, if the decision makers are cost-sensitive, they tend to choose a higher weight of total costs.

However, we found that the results from NSGA-II are not very sensitive to the weight changing from 0.1 to 0.9. Within the weight interval [0.1, 0.4] and [0.6, 0.9], the compromise solutions of a Pareto solution set do not change and the corresponding total costs do not increase even though the decision maker has a risk-seeking tendency. These data are consistent with the notion that the compromise solution is relatively stable, which makes it easier for the decision maker to select the final SAR scheme.

During an actual decision-making process for SAR in maritime emergency, decision makers must artificially adjust and optimize the scheme to select vessels and aircrafts as soon as possible. Consider a scenario in which decision makers have some specific requirements, such as: (1) if three “Beihai rescue 116” must participate in the SAR operation, then the number encoding of $x_A$ is set to 3 when initializing the population; and (2) if the SAR task need coordination of two kinds of vessels, then the encoding of them are linked to satisfy this requirement. The proposed decision support method in this paper has enough flexible space to be applied in practice when other similar situations occur. The decision support model and the corresponding solving algorithm allow users to set specific encoding and adjust the SAR schemes based on individual preferences.

5. Conclusions

The main contribution of this paper is to propose a decision support method to help design and operationalize the SAR plan in a maritime emergency based on intelligent algorithms and TOPSIS. Specifically, the three-stage framework, including the factors integration, identification of variables and model solving, is described step by step. In order to develop an intelligent algorithmic-based decision support method for SAR, we investigate two important aspects: (1) how to organize and optimize the number and types of SAR resources to execute the search task; (2) how to balance different objectives when allocating SAR resources under different decision preferences. The process of generating probability distribution maps and determining the search areas are also discussed before investigation of the SAR resources optimization. By introducing the POC, POD, probability of survival, success rate and costs, a single objective model and a multi-objective model are both designed and discussed in this paper. From the comparison of search efforts and simulations of search task assignments, the proposed method can help to make the final search plan quickly and effectively.

The proposed decision support method can be applied to the maritime SAR emergency response. However, one important future work of SAR research may focus on extending our decision model to consider SAR cooperation behavior, defining uncertain environmental- or human factors, and enabling multi-decision makers to work together. In the future, an agent-based simulation framework could be developed to realize the intelligent interaction between resources and decision makers. Moreover, this method should be applied to more maritime emergencies for further validation in the future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence
CRediT authorship contribution statement

Weitao Xiong: Conceptualization, Methodology, Software, Data curation, Visualization, Investigation, Validation, Writing - original draft, Writing - review & editing. P.H.A.J.M. van Gelder: Supervision, Methodology, Writing - review & editing. Kewei Yang: Data curation, Software.

Acknowledgements

The work was supported by the National Key R&D Program of China (Grant No.2017YFC1405005), National Science Foundation of China (Grant No.71901215), China Scholarships Council (Grant No.201803170203).

Appendix A

Table A1

| Levels | The wave height | The corresponding wind level | Wind speed (m/s) |
|--------|-----------------|------------------------------|-----------------|
| 0      | 0               | 0                            | 0.0–0.2         |
| 1      | $\frac{1}{2}$ $H_1$ < 0.10 | 1–2                          | 0.3–3.3         |
| 2      | $\frac{1}{2}$ $H_1$ < 0.50 | 2–4                          | 1.6–7.9         |
| 3      | $\frac{1}{2}$ $H_1$ < 1.25 | 4–5                          | 5.5–10.7        |
| 4      | $\frac{1}{2}$ $H_1$ < 2.50 | 5–7                          | 8.0–17.1        |
| 5      | $\frac{1}{2}$ $H_1$ < 2.00 | 7–8                          | 13.9–20.7       |
| 6      | $\frac{1}{2}$ $H_1$ < 1.25 | 8–9                          | 17.2–24.4       |
| 7      | $\frac{1}{2}$ $H_1$ < 6.00 | 10–11                        | 24.5–32.6       |
| 8      | $\frac{1}{2}$ $H_1$ < 9.00 | 30–60 min                    | 30–90 min       |
| 9      | $\frac{1}{2}$ $H_1$ < 14.00 | 12                           | $\geq$ 32.7     |

Note: National Standard of the People’s Republic of China (GBJ-64.1.85, 64.2–85).

Table A2

| Water temperature | Exhaustion or unconsciousness in | Expected survival time |
|-------------------|----------------------------------|------------------------|
| 70–80 °F (21–27 °C) | 3–12 h                           | 3 h–indefinitely        |
| 60–70 °F (16–21 °C) | 2–7 h                            | 2–40 h                 |
| 50–60 °F (10–16 °C) | 1–2 h                            | 1–6 h                  |
| 40–50 °F (4–10 °C)  | 30–60 min                         | 1–3 h                  |
| 32.5–40 °F (0–4 °C) | 15–30 min                         | 30–90 min               |
| <32 °F (≤0 °C)     | Under 15 min                      | Under 15–45 min         |

Note: US SAR Task Force (available: http://ussartf.org/cold_water_survival.htm).

Appendix B

Table B1, B2 and B3 summarize the sweep width (nautical miles) of SAR resources.

Table B1

| The Search object | Visibility (nmi) |
|-------------------|------------------|
|                   | 3                |
|                   | 5                |
|                   | 10               |
|                   | 15               |
|                   | 20               |
| People in water   | 0.4              |
|                   | 0.5              |
|                   | 0.6              |
|                   | 0.7              |
|                   | 0.7              |

Note: National Standard of the People’s Republic of China (GBJ-64.1.85, 64.2–85).
Table B2

| The search object | Visibility (nmi) |
|-------------------|-----------------|
|                   | 1               | 3               | 5               |
| People in water   | 0.1             | 0.1             | 0.1             |

Table B3

| The search object | Visibility (nmi) |
|-------------------|-----------------|
|                   | 1               | 3               | 5               |
| People in water   | 0.1             | 0.1             | 0.1             |

According to equations (9) and (10), the coverage and POD of SAR resources can be calculated, as shown below. This is a necessary step to compute the success rate of whole SAR operation.

Table B4

| SAR resources       | Coverage | POD  |
|---------------------|----------|------|
| Vessels             | 4        | 0.98 |
| Helicopters         | 1        | 0.63 |
| Fixed-wings aircrafts | 1       | 0.63 |

Appendix C

Table C1

| Abbreviation | Full name                                      |
|--------------|-----------------------------------------------|
| ASPT         | Advanced Search Planning Tool                 |
| CANSARP      | Canadian Search and Rescue Program            |
| CASP         | Computer-Assisted Search Planning             |
| DE           | Differential evolution                         |
| DSS          | Decision support systems                      |
| GA           | Genetic Algorithm                              |
| MOOP         | Multi-Objective Optimization Problem          |
| NIMSARSS     | National Maritime Search and Rescue Support System |
| NSGA-II      | Non-Dominated Sorting Genetic Algorithm        |
| PSO          | Particle Swarm Optimization                    |
| SAR          | Search and Rescue                              |
| SAROPS       | Search and Rescue Optimal Planning System     |
| SOA          | Service-Oriented Architecture                  |
| TOPSIS       | Technique for Order Preference by Similarity to an Ideal Solution |

References

Abi-Zeid, I., Doyon, B., 2003. Using a geographic decision support system to plan search and rescue operations. Int. J. Emerg. Manag. 1 (4), 346–362.
Abi-Zeid, I., Frost, J.R., 2005. SARPPlan: a decision support system for Canadian Search and Rescue Operations. Eur. J. Oper. Res. 162 (3), 630–653.
Abi-Zeid, I., Morin, M., Nilø, O., 2019. Decision Support for Planning Maritime Search and Rescue Operations in Canada.
Abi-Zeid, I., Nilø, O., Lamontagne, L., 2011. A constraint optimization approach for the allocation of multiple search units in search and rescue operations. INFOR Inf. Syst. Oper. Res. 49 (1), 15–30.
Agbeiso Ooste, D., Li, B., Ai, B., Gao, S., Xu, J., Chen, X., Lv, G., 2019. A decision-making algorithm for maritime search and rescue plan. Sustainability 11 (7), 2084.
Ai, B., Li, B., Gao, S., Xu, J., Shang, H., 2019. An intelligent decision algorithm for the generation of maritime search and rescue emergency response plans. IEEE Access 7, 155835–155850.
Akbari, A., Pelot, R., Eiseht, H.A., 2018. A modular capacitated multi-objective model for locating maritime search and rescue vessels. Ann. Oper. Res. 267 (1–2), 3–28.
Banda, O.A.V., Goerlandt, F., 2018. A STAMP-based approach for designing maritime safety management systems. Saf. Sci. 109, 109–129.
Banda, V., Osiris, A., 2017. Maritime Risk and Safety Management with Focus on Winter Navigation.
Bickel, P., Friedrich, R., 2013. Environmental External Costs of Transport. Springer Science & Business Media.
Brevik, Ø., Allen, A.A., 2008. An operational search and rescue model for the Norwegian Sea and the North Sea. J. Mar. Syst. 69 (1–2), 99–113.

Deb, K., Agrawal, S., Pratap, A., Meyarivan, T., 2000. A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II, International Conference on Parallel Problem Solving from Nature. Springer, pp. 849–858.
Eagle, J.N., Yee, J.R., 1990. An optimal branch-and-bound procedure for the constrained path, moving target search problem. Oper. Res. 38 (1), 110–114.
Erol, S., Badar, E., 2015. The analysis of ship accident occurred in Turkish search and rescue area by using decision tree. Marit. Pol. Manag. 42 (4), 377–388.
Frost, J., 1999a. Principles of search theory, part I: Detection. Response 17 (2), 1–7.
Frost, J., 1999b. Principles of search theory, part II: effort, Coverage, and POD. Response 17 (2), 8–16.
Frost, J., Stone, L.D., 2001. Review of Search Theory: Advances and Applications to Search and Rescue Decision Support. SOZA AND COMPANY LTD FAIRFAX VA.
Gao Song, X.J., Ai, Bo, Zhong, Shan, Liu, Guiyan, 2019. National maritime search and rescue support platform based on Service-Oriented Architecture. Mar. Forecast 36 (3), 71–77.
Gomes, J.O., Borges, M.R., Huber, G.J., Carvalho, P.V.R., 2014. Analysis of the resilience of team performance during a nuclear emergency response exercise. Appl. Ergon. 45 (3), 780–788.
Guard, C.C., 1993. CANSARP V3. 2.
Guard, U.C., 1986. National Search and Rescue Manual. CG-308. Superintendent of Documents, US Government Printing Office, Washington, DC, pp. 1–2 (July 1973), with amendments.
Guo, Y., Ye, Y., Yang, Q., Yang, K., 2019. A multi-objective INLP model of sustainable resource allocation for long-range maritime search and rescue. Sustainability 11 (3), 929.
Guoxiang, L., Maofeng, L., 2010. Sargis: A GIS-Based Decision-Making Support System for Maritime Search and Rescue, 2010 International Conference on E-Business and E-Government. IEEE, pp. 1571–1574.

Hwang, C.-L., Yoon, K., 1981. Methods for Multiple Attri- bute Decision Making, Multiple Attribute Decision Making. Springer, pp. 58–191.

Jasionowski, A., 2011. Decision support for ship flooding crisis management. Ocean Eng. 38 (14-15), 1568–1581.

Koopman, B.O., 1957. The theory of search: III. The optimum distribution of searching effort. Oper. Res. 5 (5), 613–626.

Kratzke, T.M., Stone, L.D., Frost, J.R., 2010. Search and Rescue Optimal Planning System, 2010 13th International Conference on Information Fusion. IEEE, pp. 1–8.

Lu, L., Goerlandt, F., Banda, O.A.V., Kujala, P., Höglund, A., Arneborg, L., 2019. A Bayesian Network risk model for assessing oil spill recovery effectiveness in the ice-covered Northern Baltic Sea. Mar. Pollut. Bull. 139, 440–458.

McCormack, E., Elliott, G., Tikuisis, P., Tipton, M., 2008. Search and Rescue (SAR) Victim Empirical Survival Model. Report for the USCG.

Ministry of Transport in China, 2019. Statistical Information on Maritime Emergencies in China. http://zizhan.mot.gov.cn/sj2019/soujiuzx/.

Plant, K.L., Stanton, N.A., 2016. Distributed cognition in Search and Rescue: loosely coupled tasks and tightly coupled roles. Ergonomics 59 (10), 1353–1376.

Price, K., Storn, R.M., Lampinen, J.A., 2006. Differential Evolution: a Practical Approach to Global Optimization. Springer Science & Business Media.

Richardson, H.R., Dicenzo, J.H., 1980. The United States Coast guard computer-assisted search planning system (CASP). Nav. Res. Logist. Q. 27 (4), 659–680.

Srinivas, N., Deb, K., 1994. Multiobjective optimization using nondominated sorting in genetic algorithms. Evol. Comput. 2 (3), 221–248.

Storn, R., Price, K., 1997. Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. J. Global Optim. 11 (4), 341–359.

Vidan, P., Hasanapthic, N., Grbić, T., 2016. Comparative analysis of renowned softwares for search and rescue operations. NASE MORE: znanstveno-stručni casepis za more i pomorstvo 63 (2), 73–80.

Xue, J., Value Sci. Technol. (1), 5.

Xue, J., Chen, Z., Papadimitriou, E., Wu, C., Van Gelder, P., 2019a. Influence of environmental factors on human-like decision-making for intelligent ship. Ocean Eng. 186, 106060.

Xue, J., Van Gelder, P., Reniers, G., Papadimitriou, E., Wu, C., 2019b. Multi-attribute decision-making method for prioritizing maritime traffic safety influencing factors of autonomous ships’ maneuvering decisions using grey and fuzzy theories. Saf. Sci. 120, 323–340.

Zavadskas, E.K., Mardani, A., Turskis, Z., Jusoh, A., Nor, K.M., 2016. Development of TOPSIS method to solve complicated decision-making problems—an overview on developments from 2000 to 2015. Int. J. Inf. Technol. Decis. Making 15, 645–682, 03.