The Journal of Navigation (2024), **77**:4 543–558
doi:10.1017/S0373463324000365

CAMBRIDGE UNIVERSITY PRESS

RESEARCH ARTICLE

Maritime accidents-based optimal rescue ship location using dynamic programming and particle swarm optimisation algorithm

Sang-Lok Yoo,[1] and Kwang-Il Kim[2]*

[1] Future Ocean Information Technology, Jeju 63169, Republic of Korea
[2] Department of Marine Industry and Maritime Police, Jeju National University, Jeju 64343, Republic of Korea.
*Corresponding author: Kwang-Il Kim; Email: kki@jejunu.ac.kr

Received: 21 May 2023; **Revised:** 2 August 2024; **Accepted:** 25 November 2024; **First published online:** 12 March 2025

Keywords: search and rescue (SAR); operations research; optimisation; shortest path

Abstract

This study describes an optimal method for deploying rescue ships in response to marine accidents using dynamic programming and particle swarm optimisation in an archipelago. We solved the shortest distance problem from a rescue ship to a marine accident using dynamic programming, which avoids obstacles, such as land or aquacultures. The optimal location problem is NP-hard. However, the optimal locations were found to be efficient among the various candidate combinations using particle swarm optimisation. We compared two models based on the set covering location model (SCLM) and P-median model (PMM). The PMM outperformed the SCLM approach in the test. The findings of this study may be valuable for directing judgments regarding search and rescue (SAR) vessel placements to maximise resource utilisation efficiency and service quality. Furthermore, this process can flexibly arrange multiple rescue ships.

1. Introduction

In the event of a marine accident, it is imperative that rescue ships arrive at the scene promptly, as the likelihood of finding and rescuing survivors diminishes rapidly over time. Tipton and Golden (2011) state that survival is rare for individuals submerged for more than 90 min in waters warmer than 6°C. Conversely, survival is improbable for those submerged for more than 30 min in waters colder than 6°C. Therefore, in preparation for marine accidents, human and material damage can be minimised by shortening the voyage distance depending on where the rescue ships, which have limited resources, are normally placed within the jurisdiction.

If no marine accident occurs, the rescue ship will drift or sail at a low speed in a zigzag to save energy under its jurisdiction. Rescue ships have been deployed in places with easy access or heavy traffic without a theoretical basis. The deployment of rescue ships should be based on scientific standards.

Many studies have been conducted on search and rescue (SAR) plans, including the search area setting, search patterns and allocation of resources to respond to marine accidents. Astbury (1987) investigated the determination of the search area and the deployment of search units. This is an important study on the spatial deployment of search and rescue forces following an accident. However, this does not study where rescue ships are normally deployed for maritime emergencies. Several countries have established efficient automated SAR systems. The Search and Rescue Optimal Planning System (SAROPS), the successor of the Computer-Assisted Search Planning (CASP) system, was launched in October 2003, and version 1.0 was deployed in early 2007 in the US (Richardson and Discenza, 1980; Kratzke et al., 2010).

© The Author(s), 2025. Published by Cambridge University Press on behalf of The Royal Institute of Navigation

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

The Canadian Coast Guard is developing a new Advanced Search Planning Tool (ASPT) to replace the Canadian Search and Rescue Program (CANSARP) (Abi-Zeid et al., 2019). In China, a software package called SARGIS has been created to provide SAR with supporting databases, application modules and a graphical user interface (Guoxiang and Maofeng, 2010). In addition, the National Maritime Search and Rescue Support System (NMSARSS) was developed, which significantly reduces emergency response time and improves maritime SAR prediction accuracy (Xiong et al., 2020). Various studies have analysed SAR operations. The systems for SAR have similar functions: drift prediction, marine environmental forecasting visualisation and collaborative service. Previous studies focused on deploying rescue ships after marine accidents to search promptly. However, it is crucial that rescue ships are stationed inside their jurisdictions on regular days. The jurisdiction area allocated to one rescue ship is extensive and resources are limited.

Several studies have been conducted to deploy rescue ships based on historical marine accidents. Yoo and Jung (2017) proposed a *k*-means clustering method to derive the optimal location of rescue ships in normal situations. A Voronoi diagram was used to divide the jurisdictional area of each rescue ship using *k*-means clustering. However, this method is limited because it cannot be applied to areas where islands and aquaculture farms exist. Jung and Yoo (2019) proposed an image-processing approach and flood filling on numerous islands of varying sizes. The flood-filling method calculates the path between two points. Although the flood-filling technique can detour islands, the path is not the shortest distance because it uses the Manhattan distance. The path should be based on the Euclidian distance, but challenges affecting this implementation include obstacles such as islands and aquaculture farms.

This study aims to develop a model for maritime rescue resource locations waiting to respond promptly to accidents. The contributions of this study are summarised as follows: (1) dynamic programming (DP) was employed to calculate the shortest distance between two points while avoiding land obstacles; (2) particle swarm optimisation (PSO) was applied among metaheuristic methods to efficiently search for the optimal position that satisfies the objective function among numerous candidate positions composed of a grid; (3) we compare two models based on the set covering location model (SCLM) and P-median model (PMM). PMM provided solutions with significantly better performance than the SCLM-based rescue ship arrangement.

The remainder of this paper is organised as follows. Section 2 describes related works on shortest path algorithms and optimisation. Section 3 proposes a method for determining the optimal deployment positions of rescue ships in an archipelago under normal conditions. Section 4 presents the experimental results of the proposed method and discusses these findings. Finally, Section 5 concludes the study.

2. Related works

2.1. Shortest path

Path planning should derive the shortest route to the target point, and it is essential to minimise the time required to derive the route. Many methods have been used to establish path planning, such as visibility graphs, waypoint graphs and grid methods.

A visibility graph is a set of adjacency matrices for each connection node and distance information. The nodes of the visibility graph are composed of the starting point, target point and vertices of the obstacle, and the link is composed of visible lines between the nodes. The visibility graph guarantees the shortest path by using the links connecting the nodes. However, because the vertex of an obstacle is used, there is no free space in the moving path (Wang and Guo, 2003; Zhang et al., 2008). Therefore, realistically, the arrival of a rescue vessel at an obstacle node indicates a collision or stranding on an island or aquaculture farm. Meanwhile, in waypoint graphs, an edge between two waypoints indicates that the rescue ships can pass through this point safely without colliding with the region boundaries or obstructions. However, waypoint graphs do not guarantee a short distance because they do not use vertices as nodes, but instead place them at random midpoints between obstacles (Zhu et al., 2015). In places where various aquaculture farms, such as abalone and seaweed farms, are scattered, the corners

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

of the farms become hundreds of thousands or millions of nodes. Therefore, there is a problem with the amount of computation required in methods such as visibility and waypoint graphs.

Meanwhile, a grid-based node can be analysed using a detailed and consistent principle, and is particularly suitable for analysing a considerable area characterised by an open-space configuration (Akbari et al., 2018b; Lin et al., 2018). A rescue ship cannot stand still in one place, unlike a car, due to the tide, so a small drifting zone is needed for emergency response to a marine accident. Therefore, a study is required to determine the optimal location based on the grid. We chose a grid-based method in this study.

2.2. Optimisation

The placement problem is a classic optimisation problem that identifies the optimal site for a facility based on geographical requirements and transportation distances. As the location model becomes increasingly sophisticated, such as the set covering location model (SCLM) and p-median model (PMM), it has proven to be NP-hard (Megiddo and Supowit, 1984). Increasing the problem size makes it difficult for traditional optimisation approaches to handle these challenges. Therefore, diverse intelligence methods, such as PSO, genetic algorithms and the simulated annealing algorithm, have been used to solve challenging large-scale location problems (Qin et al., 2012; Alnahhal and Noche, 2015; Adeh et al., 2017).

The PSO algorithm is an evolutionary algorithm developed by Kennedy and Eberhart (1995). This optimisation technique simulates the movement of swarms of insects, birds and fish through information exchange and cooperation. Unlike other heuristic algorithms, the PSO algorithm can overcome the shortcomings of early convergence to a local solution by balancing the global and local solutions in the search space. In addition, there are advantages in that the algorithm is simple, has a relatively small number of parameters and can be implemented with simple computer coding. Therefore, in this study, PSO was applied to metaheuristic optimisation methods to efficiently determine the optimal position among the candidate positions.

3. Methodology

3.1. Preparation for modelling

The space to be analysed is divided into grids. Each grid is set as a node, which is the candidate location for the rescue ship. The graph is a set of adjacency matrices of each connection pair and distance information, including information on connection pairs that have a relationship with the nodes. Nodes on land, aquaculture farms, shorelines and obstacles other than the sea are excluded from the node candidates.

Knowing that an accident occurs in a specific area does not mean that it will happen again in the same place, nor does it mean that the accident cannot be in another location if it did not happen in the past. Therefore, it is appropriate to simulate the distribution of potential accidents in the study area using statistical estimates from historical data to address this problem. Furthermore, because patterns of past accidents are potent predictors of the future, it is essential to extract the underlying distributions of the positions of past accidents as the basis for a probabilistic approach to generating future accidents (Akbari et al., 2018a, 2018b). The extraction of distributions from past accidents can be accomplished using a two-dimensional kernel density estimator (KDE), which is a non-parametric method for estimating the probability density function.

3.2. Objective function

In this study, we consider two classic location models, SCLM and PMM, which are adjusted and applied to our problem characteristics. SCLM determines the rescue ship location and the required vessels

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

(Roth, 1969; Toregas et al., 1971). SCLM ensures that every demand point is covered at least once. PMM minimises the total or average distance between p facilities and every demand location (Hakimi, 1965).

The objective functions of SCLM and PMM were designed such that all marine accidents can be serviced within a given time. First, a rescue ship was dispatched close to the marine accident location. If there is only one rescue ship owing to bad weather or repair of a rescue ship in the jurisdictional area, the constraint condition is designed to arrive within 1·5 h based on a maximum speed of 30 knots. However, in the case of two or more rescue ships, the constraint condition was designed such that it could be reached within 1 h.

The objective function for the SCLM is given by Equation (1) (Caprara et al., 2000). Let c_r denote the r-th grid node location for the rescue ship, which is the starting point. In addition, y_m denotes the m-th grid node location for an estimated marine accident site, which is a destination.

$$argmin_{c_1,\, c_2,\, \ldots\, ,\, c_r} \left\{ \sum_{m=1}^{l} \min(||c_1 - y_m||, ||c_2 - y_m||, \cdots, ||c_r - y_m||) \right\} \tag{1}$$

subject to

$$\min(||c_1 - y_m||, ||c_2 - y_m||, \cdots, ||c_r - y_m||) < \theta, \theta = \begin{cases} 45\,\text{nm} & \text{for } r = 1 \\ 30\,\text{nm} & \text{otherwise} \end{cases}$$

Here, $||\cdot||$ is calculated by the theory of the spherical law of cosines using Equation (2) (Ramachandran et al., 2005). Let p_g^{lat} and p_g^{lon} denote GPS latitude and longitude at the g-th node, respectively, and p_{g+1}^{lat} and p_{g+1}^{lon} indicate those respective coordinates at the next node.

$$||\cdot|| = \sum_{g=1}^{G} e \arccos\{\sin(p_g^{lat})\ \sin(p_{g+1}^{lat}) + \cos(p_g^{lat})\ \cos(p_{g+1}^{lat})\ \cos(p_g^{lon} - p_{g+1}^{lon})\} \tag{2}$$

where $||\cdot||$ is the sum of distances between nodes. The shortest distance means that the destination is reached through several waypoints from the starting point. Here, G represents the total number of nodes, including the starting node, several waypoint nodes and the destination node. Additionally, G is two if it is possible to go directly from the starting point to the destination without obstacles and e denotes Earth's radius.

Unlike SCLM, PMM considers the estimated probability density required to reflect marine accident demands. The estimated probability density of each grid can be calculated using the KDE from historical marine accidents. The estimated probability density is used as the demand weight in the objective function. The objective function for PMM is given by Equation (3) (Mladenović et al., 2007). The objective function serves to find the location of rescue ships in the jurisdictional area with the shortest cumulative distance for all marine accident demands. Here, $\tau(y_m)$ is the density of the accidents estimated using the KDE at the m-th grid node and l is the total number of candidate nodes for the rescue ship arrangement.

$$argmin_{c_1,\, c_2,\, \ldots\, ,\, c_r} \left\{ \sum_{m=1}^{l} \min(||c_1 - y_m||, ||c_2 - y_m||, \cdots, ||c_r - y_m||)\ \tau(y_m) \right\} \tag{3}$$

subject to

$$\min(||c_1 - y_m||, ||c_2 - y_m||, \cdots, ||c_r - y_m||) < \theta,\ \theta = \begin{cases} 45\ \text{nm} & \text{for } r = 1 \\ 30\ \text{nm} & \text{otherwise} \end{cases}$$

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

where $\tau(y_m) = \frac{1}{Nb^2}\sum_{n=1}^{N}\varphi\left(\frac{y_m - z_n}{b}\right)$, N is the number of marine accidents in the study area, z_n denotes the location of an n-th actual marine accident and φ is the kernel function. A Gaussian kernel is used to estimate the density function and b indicates the bandwidth. A horizontal grid spacing was used as the bandwidth.

3.3. Comparison criteria

It is essential to arrive at a site within the golden time to save life. The access time, also referred to as the response time for marine accidents, can be minimised by shortening the voyage distance depending on the location of the rescue ships. The average access time is frequently used as a model criterion in location studies (Akbari et al., 2018a). This criterion assesses the time required for the nearest response vessel to arrive at a marine accident site, as given by (Akbari et al., 2018b)

$$\text{Average access time} = \frac{1}{T}\sum_{t=1}^{T}\frac{d_t}{h} \tag{4}$$

where d_t is the distance between the closest rescue ship and t-th marine accident demand, T is the total marine accident demand and h is the speed of the rescue ship.

3.4. Dynamic programming

DP methods are applied to determine the shortest distance between a rescue ship and a marine accident. DP is used extensively in optimisation problems (Bellman, 1966). The shortest-path problem has an optimal substructure. For example, suppose $s \to u \to v$ is the shortest path from s to v. Node s for a rescue ship, which is the start position; node v for a marine accident, which is the destination; and node u for waypoints. The shortest path from node s to node v that uses only up to u intermediate nodes is the shortest path that either does not use node u at all or consists of the merging of the two path node s to node u and node u to node v. Let $\delta_k(s,\ v)$ be the shortest $s \to v$ path using $\leq k$ edges. This problem is similar to finding several paths from a rescue ship position to a marine accident with k edges, in which we have to find the total number of paths. Therefore, for this problem, the shortest path is one of the paths with the lowest distance. Based on this optimal substructure, we can determine the recursive Equation (5) of the single-source shortest path problem as follows (Denardo, 2012):

$$\delta_k(s,\ v) = \min\{\delta_{k-1}(s,\ v),\ \delta_{k-1}(s,\ u) + \delta_{k-1}(u, v)\ |(u,\ v) \in E\} \tag{5}$$

This step initialises the distances from the rescue ship to marine accidents as infinite and the distance to the rescue ship itself as 0. The base cases are

$$\delta_0(s,\ v) = \infty \text{ for } v \neq s$$

$$\delta_k(s,\ s) = 0 \text{ for any } k = 0 \text{ for any } k$$

We use an adjacency matrix to represent the edge information if an edge between two arbitrary nodes is connected in the graph. If there is an edge from node s to node v in the graph, the value is 1; if there are no edges from node s to node v in the graph, the value is 0. Some accidents within the aquaculture farms may not have connectable nodes. These accidents were resolved by relocating to the nearest connectable node. The distance between two nodes is calculated using the spherical law of cosines based on the GPS coordinates formed by two components: latitude, giving the north-south position, and longitude, giving the east-west position (Ramachandran et al., 2005). The unit of distance was converted to nautical miles (nm). The following Algorithm 1 of DP was used to compute the shortest path.

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

Algorithm 1. Shortest path with dynamic programming.

input: s for node of a rescue ship
v for node of a marine accident
A for adjacency matrix with each node
p^{lat}, p^{lon} for GPS positions at each node
output: d for distance between a rescue ship position and a marine accident position
begin
1. $s \leftarrow$ node number for rescue ship
2. $v \leftarrow$ node number for marine accident
3. distance table $\leftarrow [s, 0]$
4. node table $\leftarrow [s, NaN]$
5. **function shortest_path** (A, v, distance table, node table)
6. $j \leftarrow$ index of node v in the node table
7. **if** ! IsEmpty(j)
8. $d \leftarrow$ distance table[j, 2]
9. **else**
10. distance table[end+1, :] $\leftarrow [v, \infty]$
11. node table[end+1, :] $\leftarrow [v, NaN]$
12. $u \leftarrow$ finding a connected node with v in the adjacency matrix
13. $j \leftarrow$ last index of the node table
14. **for** $i = 1$ to length of u
15. **shortest_path** (A, $u[i]$, distance table, node table)
16. $e \leftarrow$ radius of Earth
17. $d' \leftarrow \arccos\{\sin(p_v^{lat})\sin(p_{u[i]}^{lat}) + \cos(p_v^{lat})\cos(p_{u[i]}^{lat})\cos(p_v^{lon} - p_{u[i]}^{lon})\} \times e + d$
18. **if** $d' <$ distance table[j, 2]
19. distance table[j, 2] $\leftarrow d'$
20. node table[j, 2] $\leftarrow u[i]$
21. **end if**
22. **end for**
23. $d \leftarrow$ distance table[j, 2]
24. **end if**
25. **end function**
26. **return** distance of node v in the distance table
end

3.5. Particle swarm optimisation

The total number of candidate nodes for rescue ships is l. All possible combinations of the number of rescue ships r elements out of the total number of candidate nodes l are countless. Therefore, we randomly sampled with a particle swarm size (q) among the total number of candidate nodes to apply PSO. The sampled matrix, X, indicates the initial particle swarm position. Subsequently, the position and velocity of each particle were updated repeatedly. Therefore, each particle has a fitness value calculated using a fitness function and finds the best position. The best position of each particle, which is the local best, is integrated into one matrix, X^{pbest}. The global best position of the entire swarm is denoted by $\mathbf{x}^{gbest} = (x_1, x_2, \ldots, x_r)$. In particular, the velocity of a particle is influenced by certain components. First, the inertia weight (w) determines the confidence of a particle in its movement, which is unaffected by X^{pbest} and $\mathbf{x}^{gbest}$. Second, the acceleration coefficients (λ_1, λ_2) determine the extent to which a particle is influenced by the memory of its best solution.

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

Algorithm 2. Particle swarm optimisation for PMM.

input: D[1..l , 1..l] for distance matrix between a node of rescue ships and estimated accidents
X for the swarm position
V for the swarm velocity
r for the total number of rescue ships deploying in the jurisdiction area
X^{pbest} for each particle best position
output: $\mathbf{x}^{gbest}$ for global best position
begin
$q \leftarrow$ particle swarm size
$w_{max} \leftarrow$ maximum inertia weight, $w_{min} \leftarrow$ minimum inertia weight
$\lambda_1, \lambda_2 \leftarrow$ acceleration coefficients
Initialise X[1..q, 1 . . . r] to be random number between 1 and the total number of nodes
Initialise T[1..q, 1 . . . r] to be zero
$X^{pbest} \leftarrow X$
$\mathbf{x}^{gbest} \leftarrow$ select one row from X
fval[1..q] $\leftarrow \infty$
fitness_local[1..q] $\leftarrow \infty$
fitness_global $\leftarrow \infty$
for $i = 1$ to maximum number of iterations
for $k = 1$ to q
$\mathbf{x} \leftarrow X_i[k]$
$D' \leftarrow D[\mathbf{x}]$
$fitness_min \leftarrow$ clustering each marine accident to a rescue ship with min(D′)
if IsEmpty(constraint distance < $fitness_min$)
$fval[k] \leftarrow \sum_{m=1}^{l} fitness_min \times \tau(y_m)$
end if
if *fval*[k]<*fitness_local*[k]
$X_{i,k}^{pbest} \leftarrow X_{i,k}$
fitness_local[k] $\leftarrow$ *fval*[k]
end if
end for
$[fitness_min, index_x^{gbest}] \leftarrow \min(fitness_local)$
if *fitness_min*≤*fitness_global*
$\mathbf{x}^{gbest} \leftarrow X_{i,k}[index_x^{gbest}]$
fitness_global ← *fitness_min*
end if
$w \leftarrow (w_{max} - w_{min})(i/\max \text{interation})^2 - (w_{max} - w_{min})(2i/\max \text{iteration}) + w_{max}$
$\mathbf{a}_1[1..q], \mathbf{a}_2[1..q] \leftarrow$ random number in the range [0,1]
$V_{i,k} \leftarrow wV_{i,k} + \lambda_1 \mathbf{a}_1 (X_{i,k}^{pbest} - X_{i,k}) + \lambda_2 \mathbf{a}_2 (\mathbf{x}^{gbest} - X_{i,k})$
$X_{i,k} \leftarrow X_{i,k} + V_{i,k}$
end for
end

Shi and Eberhart showed that PSO with linearly decreasing inertia weight performs better than PSO with fixed inertia weight (Shi and Eberhart, 1998). They varied the inertia weight linearly from 0·9 ($w_{\max}$) to 0·4 ($w_{\min}$) in the run and fixed the acceleration coefficients (λ_1, λ_2) at 2·0 (Shi and Eberhart, 1999). Here, w is an inertia weight that adjusts the strength of the previous velocity with

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

respect to the current velocity and plays an essential role in the convergence of the PSO algorithm. If the inertia weight is significant, the global search is strengthened; if it is set to a small value, the local search is intensified. However, a global solution may not be obtained if an inappropriate value is selected. Various methods exist for determining inertia weight (Tian and Shi, 2018). This study chose inertia weight as a significant value at the beginning of the search, and the inertia weight decreased nonlinearly as the search proceeded. The global search was strengthened in the initial stage and, as the iterations progressed closer to the optimal solution, the local search was given more weight (Guimin et al., 2006). The following Algorithm 2 uses PSO to efficiently find the optimal position for PMM.

4. Case study

4.1. Data collection

The area under study, namely the Wando County, South Korea, comprises 264 islands. In addition, a national marine park is situated in the coastal waters of Wando, Jeollanam Province. This park is an active seaweed farm in the South Korean coastal waters. Furthermore, 80% of South Korea's abalone production is produced in Wando County. Consequently, there are 8,100 fishing vessels in this region (Ock, 2010; Yoo and Jung, 2017).

The open ocean of Wando in the South Sea of Korea is one of the most significant shipping regions in the world, connecting China, Japan, Russia and South Korea. Consequently, an increase in the volume of vessel traffic results in a proportional increase in the number of marine accidents. In particular, approximately 2,000 Chinese fishing boats navigate through this area for fishing in eastern North Korea every year. As a result, near collisions with merchant ships occurred frequently, with a total of three collisions. The research region consists of multiple islands and a complex coastline located between latitudes 33·9° and 34·6° north and longitudes 126·2° and 127·2° east.

Figure 1 shows the process of overlaying the three databases. First, satellite and aerial photographs of the study area were processed to determine the locations of the aquaculture farms. In this procedure, we constructed an integrated aquaculture farm database after collecting data for abalone, laver, oyster, seaweed, etc. (Yoo and Jung, 2017). Second, the coastline of the research area was obtained from electronic navigational charts (ENC). Third, we analysed marine accidents between 1997 and 2016 on numerous islands in Wando County, South Korea (KMST, 2016).

Three coast guard rescue ships were specifically stationed in this maritime area for search and rescue operations. The nearest of the three rescue ships was allocated to the rescue mission and dispatched immediately to the accident location. We spaced the grid node in the study area and marked it as a candidate node for the rescue ship in the absence of obstacles. We set the grid node interval to 1·65 nm in the direction of the longitude and latitude in the study area. Figure 2(a) shows a scatter plot of the candidate nodes for rescue ships on the grid (red dots) and marine accidents (blue dots) in the study area. Figure 2(b) shows the distribution plot of the integrated aquaculture farms, including abalone, laver, oyster, seaweed farms, etc.

4.2. Future demand using kernel density estimation

The assumptions considered in this study are as follows.

(1) The average speed from the location of the rescue ship to the site of the marine accident was the same for all rescue ships.
(2) If only one rescue vessel is deployed in the waters under jurisdiction, the time required to arrive at the accident should be within 1·5 h. If two or more ships are deployed, the time required should be within 1 h.
(3) Marine weather, such as wind speed, wind direction, current speed, current direction and wave height, was not reflected.

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

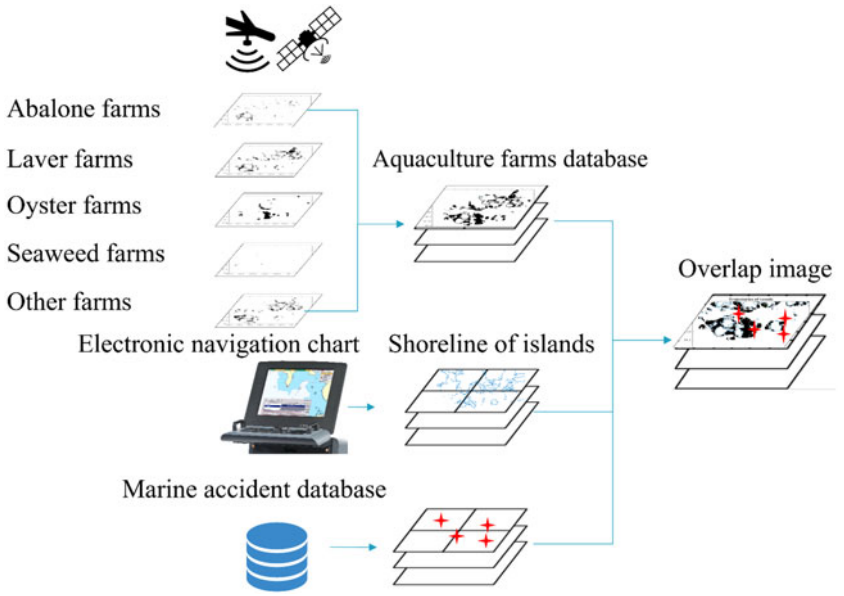


Figure 1. *Procedure of overlaying three databases: aquacultures, shorelines of islands and marine accidents.*

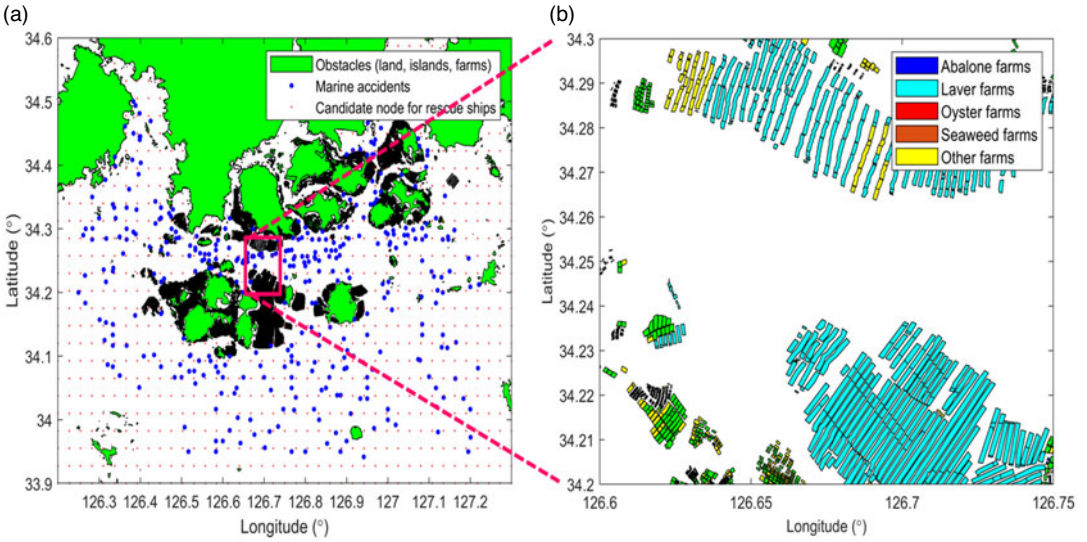


Figure 2. *Study area: (a) scatter plot of the candidate nodes for rescue ships on the grid (red dots) and marine accidents (blue dots); (b) distribution plot of the integrated aquaculture farms.*

(4) After the rescue ship received the marine accident report, the time to prepare for the travel movement was not considered.

Kernel density estimates serve the demand for generating random marine accidents in future scenarios. Using past marine accidents to predict future demand, as most studies have done, implies that the future will behave identically to the past. In the study region, 439 marine accidents have occurred over the past two decades. The density estimates applied in this study were calculated based on collisions, grounding, fires, explosions, engine failures, steering gear damage and floating object accidents, and the weights

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

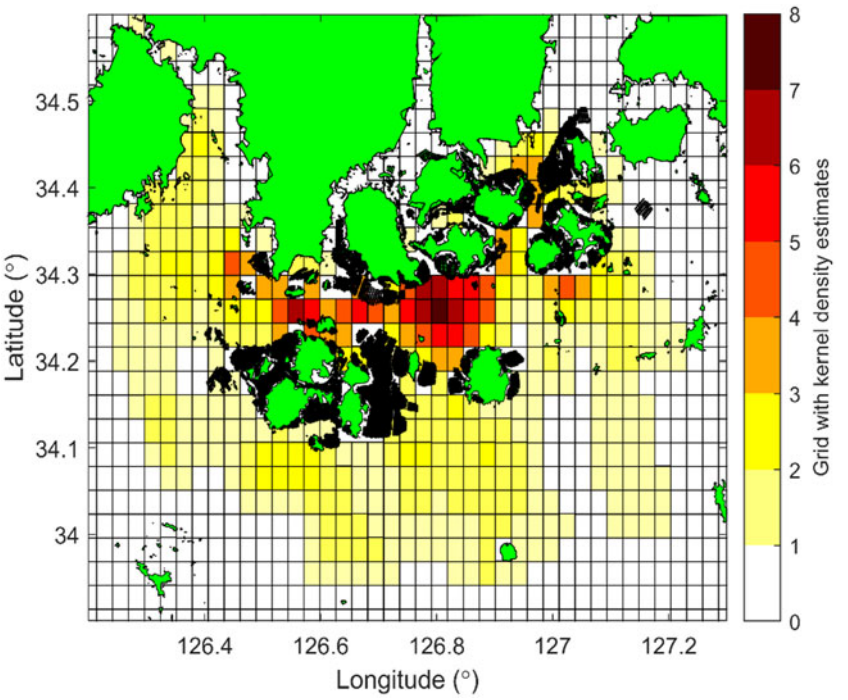


Figure 3. *Kernel estimates for marine accidents on a gridded map.*

for each factor were not considered. This is because, regardless of the severity of any marine accident, rescue ships guarding within their jurisdiction are obliged to go to the accident site when a report is received (Figure 3).

For the kernel density calculations, the centre of each grid, which is the candidate node for stationing rescue ships, was used. A Gaussian kernel was used for the density estimation. The bandwidth b of a kernel function is applied as a grid cell size of 1·65 nm. Figure 4 shows each kernel density estimate at the centre of the grid cell. In total, 1,030 marine accidents were estimated to occur in the study area. The density estimate of marine accidents is shown to be high at 34·2° to 34·3° N, where ship traffic is frequent.

4.3. Performance evaluation

The program was executed on a PC with an Intel Xeon E5-2650 v3 processor (10 CPU cores, 16 × 8 GB DDR4 RAM, 2·3 GHz). We set the particle swarm size (q) parameter to 1,000 and the number of iterations to 100. Figure 4 shows a scatter plot of the initial position of the particle swarm at the initial iteration for the PMM when the three rescue ships were deployed. Figure 5 shows a scatter plot of the last position of the particle swarm and the global best at the last iteration under the same conditions. As the number of iterations increased, the diverged particles converged around the global best solution. The global best solution for the PMM was $\mathbf{x}^{gbest} = (177, 365, 526)$.

Table 1 lists the average access time to the location of future marine accidents based on the number of rescue ships. When only one or two rescue ships were deployed, the optimal locations based on SCLM and PMM were the same, resulting in the same average access time. However, when more than three rescue ships were deployed, the average access time differed by more than 3 min.

Figure 6 shows the candidate nodes for deploying rescue ships (red dots) and the optimal locations for rescue ships based on PMM (red diamonds) in the study area. Marine accidents were naturally allocated and clustered to rescue ships in cyan, magenta and blue. This suggests that the jurisdiction

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

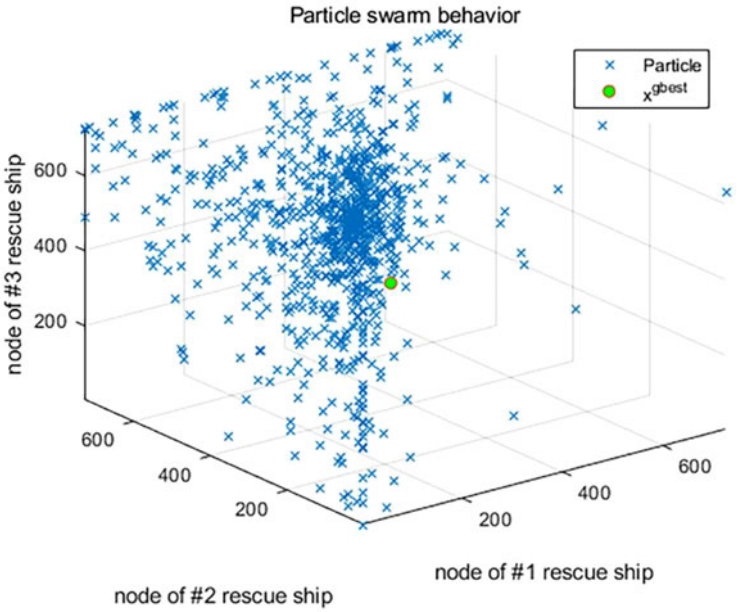


Figure 4. *Scatter plot for the position of the particle swarm at the initial iteration for PMM; the initial position of each particle is indicated with a blue cross mark and the global position with a green circle.*

Table 1. *Comparative experiments with an average access time (m) for SCLM and PMM.*

	Average access time (m) by the number of rescue ships (r)				
Model	$r=1$	$r=2$	$r=3$	$r=4$	$r=5$
SCLM	29·7	21·8	20·9	18·5	16·0
PMM	29·7	21·8	17·0	14·6	12·9

of each rescue ship could be divided. The brown line indicates the shortest path that detours around obstacles from a rescue ship to a marine accident. The sample in Figure 6 shows the distance of 14·9 nm from a rescue ship to a marine accident. It can be confirmed that the closest rescue ship reached the marine accident at the shortest distance by navigating around obstacles such as islands and fish farms.

Figure 7 shows the optimal location based on SCLM and PMM. According to Figure 3, there is a high demand for marine accidents at 34·2° to 34·3° N. Therefore, the optimal location of the PMM-based two or three rescue ships is arranged at 34·2° to 34·3° N in Figures 7(b), 7(d) and 7(f). Conversely, the location of the SCLM-based rescue ship is arranged such that it can arrive within a limited time of 1 h. Therefore, a sufficient distance is maintained between the rescue ships such that at least one rescue ship is assigned to any location of a possible marine accident.

4.4. Discussion

This study investigated an optimal method for deploying rescue ships in response to marine accidents using DP and PSO within an archipelago. The primary focus was to address the shortest distance problem from a rescue ship to a marine accident while avoiding obstacles such as land or aquaculture farms. Through the application of dynamic programming, we were able to determine the shortest paths

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

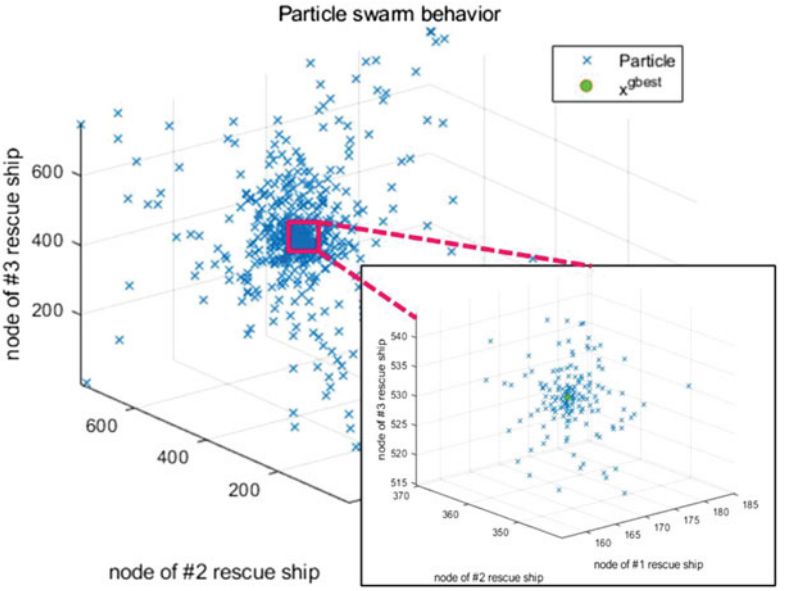


Figure 5. *Scatter plot for the position of the particle swarm at the last iteration for PMM; the last position of each particle is indicated with a blue cross mark and the global best position with a green circle.*

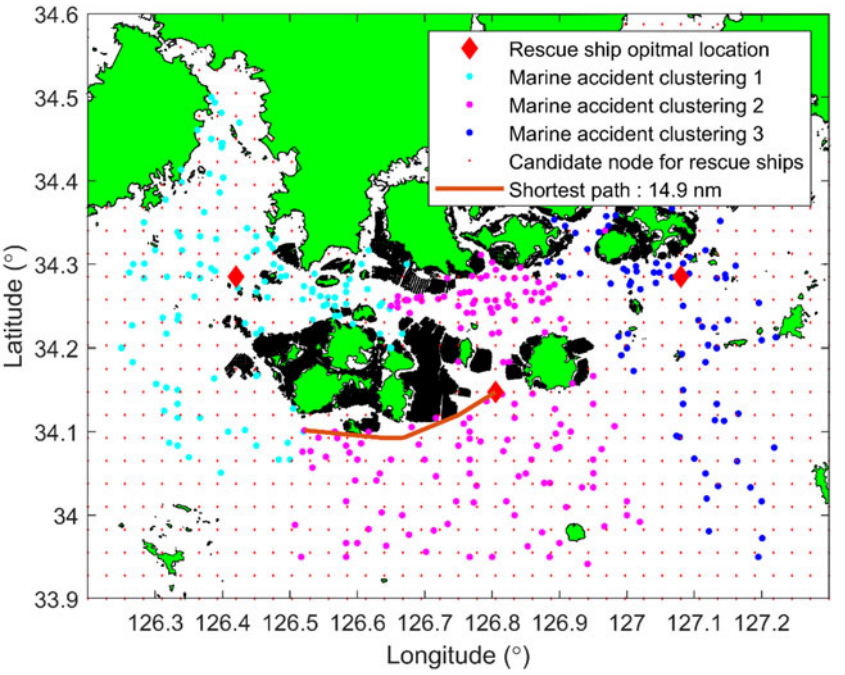


Figure 6. *Optimal locations for rescue ships (red diamonds) based on PMM, candidate node for deploying a rescue ship (red dot), actual marine accident location clusters (cyan, magenta, blue) and shortest path from a rescue ship to a marine accident (brown line).*

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

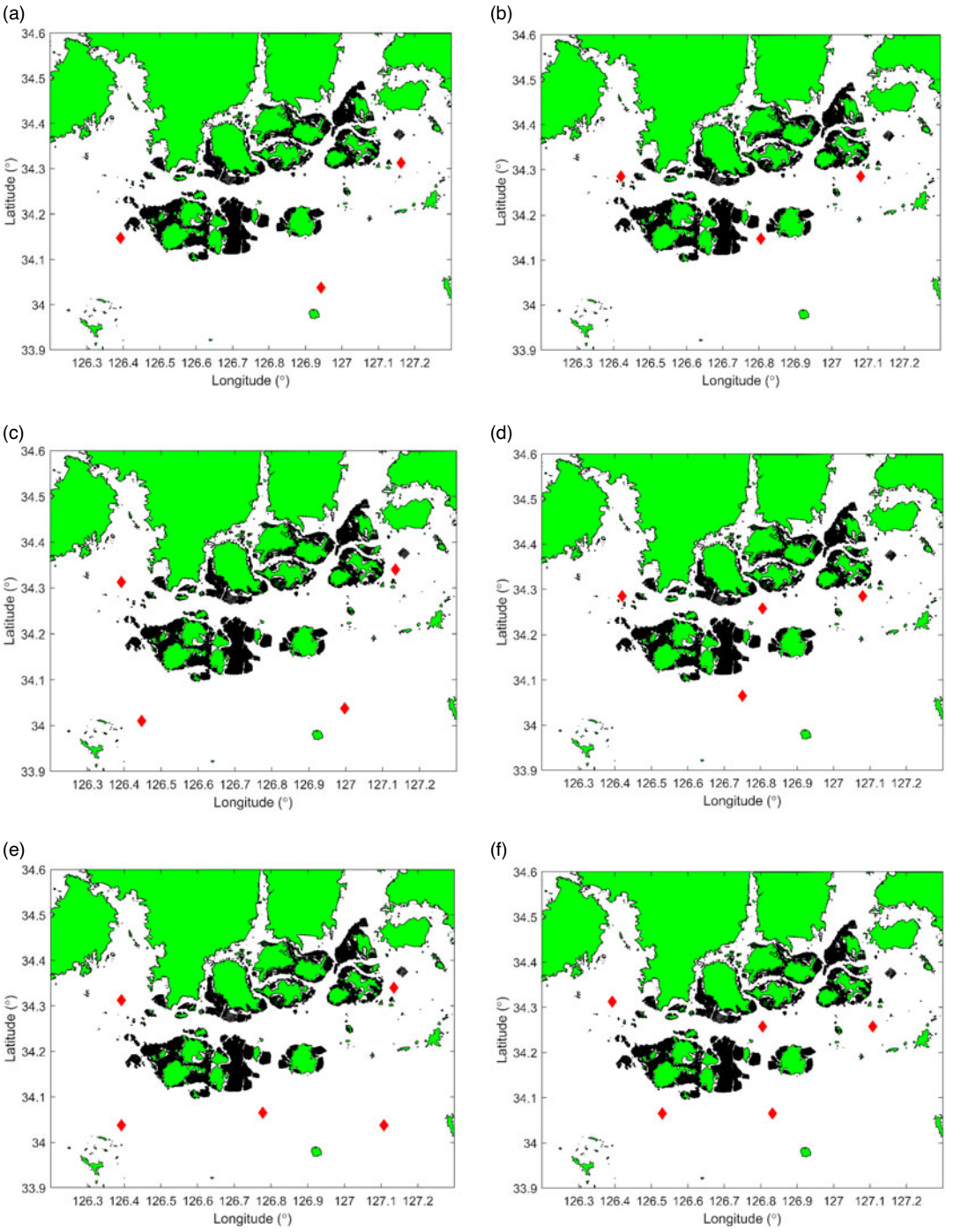


Figure 7. *(a), (c) and (e) Optimal locations (red diamonds) of the SCLM-based on the number of rescue ships. (b), (d) and (f) Optimal locations (red diamonds) of the PMM-based model by the number of rescue ships.*

efficiently. Additionally, the PSO algorithm was used to find optimal deployment locations, tackling the NP-hard nature of the problem by efficiently searching through numerous candidate combinations. The comparison between SCLM and PMM demonstrated that the PMM provided significantly better

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

performance. This superior performance suggests that the PMM is more effective in optimising rescue ship placement, potentially leading to faster response times and improved resource utilisation.

Despite the promising results, there are several limitations to this study. First, the study did not consider the diverse characteristics of different types of rescue ships and accidents. The absence of detailed information on the specific capabilities and limitations of various rescue vessels, as well as the nature of different marine accidents, limits the granularity and realism of the analysis. Future research should incorporate these variables to enhance the accuracy and applicability of the model. Second, the model did not account for real-time marine weather conditions such as wind speed, wind direction, current speed, current direction and wave height. These factors significantly impact the movement and effectiveness of rescue operations. Integrating real-time environmental data into the model would provide a more comprehensive and dynamic solution. Third, the study assumed that the average speed from the location of the rescue ship to the site of the marine accident was the same for all rescue ships. In reality, variations in ship speed due to different ship types and sea conditions could affect the response times. Future models should consider these variations to provide a more precise estimation of arrival times. Lastly, the study's approach to predicting future marine accidents relied heavily on historical data, assuming that future incidents will follow similar patterns. While historical data is a strong predictor, it does not account for new trends or changes in maritime activities that could alter accident patterns. Incorporating trend analysis and exposure metrics such as traffic levels could improve the model's predictive capabilities.

5. Conclusions

This study describes an optimal method for deploying rescue ships in response to marine accidents using DP and PSO in an archipelago. We solved the shortest distance problem from a rescue ship to a marine accident using dynamic programming, which avoids obstacles such as land or aquacultures. The optimal location problem was NP-hard. However, the optimal locations were found to be efficient among the various candidate combinations using PSO. We compared two models based on SCLM and PMM. PMM provided solutions with significantly better performance than the SCLM-based rescue ship arrangement.

The findings of this study can assist in guiding decisions on SAR vessel deployment to improve resource utilisation and service quality. In particular, the results of this study can offer the Coast Guard important information for selecting suitable stations for the placement of new rescue ships. This process can be flexibly applied to arrange one to five rescue ships. In addition, it can aid in managing current operations to improve resource use and effectiveness. As a result, the overall reduction in the operating costs of rescue ships is shown.

One crucial factor that can make the analysis more realistic and valuable is the consideration of the different characteristics of ships and accidents. Unfortunately, this study cannot do this because the necessary information is unavailable. In addition, by modelling trends in marine accidents, accident rates and exposure metrics such as traffic levels, the proposed model can be expanded to accommodate future response needs.

Acknowledgment. None.

Funding. This research was supported by 'Regional Innovation Strategy (RIS)' through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (MOE) (2023; RIS-009) and was a part of the project titled, 'Development of AI Based Smart Fisheries Management System (2021; 0499)' which is funded by the Ministry of Oceans and Fisheries, Korea.

Competing interest. None.

References

Abi-Zeid, I., Morin, M. and Nilo, O. (2019). Decision Support for Planning Maritime Search and Rescue Operations in Canada. *Proceedings of the 21st International Conference on Enterprise Information Systems*, 328–339.

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

Adeh, I. M., Baroughi, F. and Alizadeh, B. (2017). A modified particle swarm optimization algorithm for general inverse ordered p-median location problem on networks. *Facta Universitatis, Series: Mathematics and Informatics*, **32**(4), 447–468.

Akbari, A., Eiselt, H. A. and Pelot, R. (2018a). A maritime search and rescue location analysis considering multiple criteria, with simulated demand. *INFOR: Information Systems and Operational Research*, **56**(1), 92–114. doi:10.1080/03155986.2017.1334322

Akbari, A., Pelot, R. and Eiselt, H. A. (2018b). A modular capacitated multi-objective model for locating maritime search and rescue vessels. *Annals of Operations Research*, **267**(1-2), 3–28. doi:10.1007/s10479-017-2593-1

Alnahhal, M. and Noche, B. (2015). A genetic algorithm for supermarket location problem. *Assembly Automation*, **35**(1), 122–127. doi:10.1108/AA-02-2014-018

Astbury, J. (1987). Search area determination and search unit deployment. *The Journal of Navigation*, **40**(1), 63–72. doi:10.1017/S0373463300000308

Bellman, R. (1966). Dynamic programming. *science*, **153**(3731), 34–37. doi:10.1126/science.153.3731.34

Caprara, A., Toth, P. and Fischetti, M. (2000). Algorithms for the set covering problem. *Annals of Operations Research*, **98**(1), 353–371. doi:10.1023/A:1019225027893

Denardo, E. V. (2012). *Dynamic Programming: Models and Applications*. Englewood Cliffs, NJ: Prentice-Hall.

Guimin, C., Jianyuan, J. and Qi, H. (2006). Study on the strategy of decreasing inertia weight in particle swarm optimization algorithm. *Journal-Xian Jiaotong University*, **40**(1), 53.

Guoxiang, L. and Maofeng, L. (2010). SARGIS: A GIS-Based Decision-Making Support System for Maritime Search and Rescue. In *2010 International Conference on E-Business and E-Government*, 1571–1574. doi:10.1109/ICEE.2010.398

Hakimi, S. L. (1965). Optimum distribution of switching centers in a communication network and some related graph theoretic problems. *Operations Research*, **13**(3), 462–475. doi:10.1287/opre.13.3.462

Jung, C. Y. and Yoo, S. L. (2019). Optimal rescue ship locations using image processing and clustering. *Symmetry*, **11**(1), 32. doi:10.3390/sym11010032

Kennedy, J. and Eberhart, R. (1995). Particle Swarm Optimization. *Proceedings of ICNN'95-International Conference on Neural Networks*, Vol. **4**, 1942–1948.

KMST (2016). *Accident Position Information based on Electronic Chart*. Sejong: Korea Maritime Safety Tribunal. Available at: http://data.kmst.go.kr/WebVMS_KMST/WebVMS.jsp [Accessed 12 Jan. 2016].

Kratzke, T. M., Stone, L. D. and Frost, J. R. (2010). Search and Rescue Optimal Planning System. In *2010 13th International Conference on Information Fusion*, 1–8. doi:10.1109/ICIF.2010.5712114

Lin, Q., Song, H., Gui, X., Wang, X. and Su, S. (2018). A shortest path routing algorithm for unmanned aerial systems based on grid position. *Journal of Network and Computer Applications*, **103**, 215–224. doi:10.1016/j.jnca.2017.08.008

Megiddo, N. and Supowit, K. J. (1984). On the complexity of some common geometric location problems. *SIAM Journal on Computing*, **13**(1), 182–196. doi:10.1137/0213014

Mladenović, N., Brimberg, J., Hansen, P. and Moreno-Pérez, J. A. (2007). The p-median problem: A survey of metaheuristic approaches. *European Journal of Operational Research*, **179**(3), 927–939. doi:10.1016/j.ejor.2005.05.034

Ock, Y. S. (2010). Pending issues and policy about abalone culture. *Policy Res Fish*, **5**, 13–36.

Qin, J., Ni, L. L. and Shi, F. (2012). Combined simulated annealing algorithm for the discrete facility location problem. *The Scientific World Journal*, **2012**, 1–7. doi: 10.1100/2012/576392

Ramachandran, S., Deshpande, O., Roseman, C. C., Rosenberg, N. A., Feldman, M. W. and Cavalli-Sforza, L. L. (2005). Support from the relationship of genetic and geographic distance in human populations for a serial founder effect originating in Africa. *Proceedings of the National Academy of Sciences*, **102**(44), 15942–15947. doi:10.1073/pnas.0507611102

Richardson, H. R. and Discenza, J. H. (1980). The United States coast guard computer-assisted search planning system (CASP). *Naval Research Logistics Quarterly*, **27**(4), 659–680. doi:10.1002/nav.3800270413

Roth, R. (1969). Computer solutions to minimum-cover problems. *Operations Research*, **17**(3), 455–465. doi:10.1287/opre.17.3.455

Shi, Y. and Eberhart, R. C. (1998). Parameter Selection in Particle Swarm Optimization. In *Evolutionary Programming VII: 7th International Conference*, San Diego, California, USA. doi:10.1007/BFb0040810

Shi, Y. and Eberhart, R. C. (1999). Empirical Study of Particle Swarm Optimization. *Proceedings of the 1999 Congress on Evolutionary Computation-CEC*99. doi:10.1109/CEC.1999.785511

Tian, D. and Shi, Z. (2018). MPSO: Modified particle swarm optimization and its applications. *Swarm and Evolutionary Computation*, **41**, 49–68. doi:10.1016/j.swevo.2018.01.011

Tipton, M. J. and Golden, F. S. C. (2011). A proposed decision-making guide for the search, rescue and resuscitation of submersion (head under) victims based on expert opinion. *Resuscitation*, **82**(7), 819–824. doi:10.1016/j.resuscitation.2011.02.021

Toregas, C., Swain, R., ReVelle, C. and Bergman, L. (1971). The location of emergency service facilities. *Operations Research*, **19**(6), 1363–1373. doi:10.1287/opre.19.6.1363

Wang, Z. and Guo, G. (2003). Present situation and future development of mobile robot navigation technology. *Robot*, **25**(5), 470–474.

Xiong, W., Van Gelder, P. H. A. J. M. and Yang, K. (2020). A decision support method for design and operationalization of search and rescue in maritime emergency. *Ocean Engineering*, **207**, 107399. doi:10.1016/j.oceaneng.2020.107399

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press

Yoo, S. L. and Jung, C. Y. (2017). Optimal arrangement of patrol ships based on k-means clustering for quick response of marine accidents. *Journal of the Korean Society of Marine Environment & Safety*, **23**(7), 775–782. doi:10.3390/sym11010032

Zhang, H., Liu, M., Liu, R. and Hu, T. (2008). Path Planning of Robot in Three-Dimensional Grid Environment Based on Genetic Algorithms. In *2008 7th World Congress on Intelligent Control and Automation*. doi:10.1109/WCICA.2008.4593059

Zhu, W., Jia, D., Wan, H., Yang, T., Hu, C., Qin, K. and Cui, X. (2015). Waypoint graph based fast pathfinding in dynamic environment. *International Journal of Distributed Sensor Networks*, **11**(8), 238727. doi:10.1155/2015/23872

Cite this article: Yoo S-L and Kim K-I (2024). Maritime accidents-based optimal rescue ship location using dynamic programming and particle swarm optimisation algorithm. *The Journal of Navigation* **77**: 4, 543–558. https://doi.org/10.1017/S0373463324000365

https://doi.org/10.1017/S0373463324000365 Published online by Cambridge University Press