Article

Research on Optimal Model of Maritime Search and Rescue Route for Rescue of Multiple Distress Targets

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Abstract: Coastal countries began to develop green energy, and offshore wind power equipment in coastal areas was gradually built. Since coastal wind power generation often requires carrying out maintenance between wind turbines with the assistance of service operation vessels, this situation may cause coastal areas to be prone to people falling into the water. However, traditional maritime search and rescue plans take a long time to gather information from man overboard incidents. In order to minimize injuries to people in distress, the maritime search and rescue process must be as short as possible. Despite that all the search and rescue plans are based on the concept of the shortest path, the efficient plans must not only consider the distance but also consider the cost of search and rescue. Therefore, this study established a set of practices applicable to the on-site commander (OSC) to dispatch rescue ships, as well as the planning of maritime search and rescue route models. Based on the easy-to-observe state of the target in distress, the model is analyzed and calculated by Floyd–Warshall algorithm and Grey relational analysis so as to sort the rescue plan and optimize the effect of the search and rescue route at sea. According to the simulation analysis, when the man overboard incident occurs in the coastal area, the OSC can immediately use this model to plan the best search and rescue route and dispatch a reasonable number of rescue ships.

Keywords: maritime search and rescue; coastal countries; rescue ships; distress targets

1. Introduction

Offshore wind power is an energy that does not emit pollutants. Some coastal countries have begun to build a large number of offshore wind power plants to develop green energy [1,2]. With related wind power facilities being widely constructed, the importance of maritime search and rescue operations is more emphasized by coastal countries. Still, research in respect of applicable search and rescue routes for wind farm personnel falling water incidents has not been proposed. A personnel falling water incident is an emergency in which a person (crew or passenger) of a vessel at sea falls into the water. This incident is one of the most common main causes of endangering the lives and safety of ship personnel at sea, particularly in large ships with slow sailing speeds, or in small ships with few personnel [3]. Under such circumstances, the vessel is built with a high risk and less protection of life and the property and environment regarding the personnel.

A maritime search and rescue operation provides reliable assistance to people in danger or at a potential risk at sea. Traditional maritime search and rescue uses factors, such as time gap, leeway, tide or currents, and swell of the distress target, to set the search datum point. The on-scene commander (OSC) uses these data to evaluate and subsequently plan a maritime search and rescue; meanwhile, it is in accordance with the international maritime organization search and rescue (IMOSAR Manual) specifications [4,5]. However, traditional search and rescue route plans require to go through the steps of spending and collecting a large amount of time and data, and then move on to the next discussion. The
“golden window” for victims is closing. The crux in the search and rescue mission is how to quickly and effectively buy time to increase the possibility of survival. From these points, maritime search and rescue plans and operations are executed on the basis of limited information. Without a complete search and rescue route planning, maritime search and rescue will be a time-consuming and resource-consuming task.

In the situation that there are multiple targets in distress at sea at the same time, if the rescue mission is still conducted as the previous search and rescue mode, the rescue time will be inevitably delayed. Hence, if the current search and rescue mode can be optimized by converting factors of the traditional maritime search and rescue mode into the rescue costs and calculating the shortest path, coastal countries will achieve search and rescue missions more objectively and quickly. This study intends to propose an optimal rescue maritime search model for persons in distress, considering the location, situation and distance so that it could assist the OSC in planning the execution and to improve the efficiency of maritime search and rescue. This model makes it easy to obtain and observe the status of the marine distress target, immediately sorts the rescue plan by the existing rescue resources, and optimizes the search and rescue route of the rescue fleet to quickly arrive at the location of the marine distress target.

In this study, the shortest path algorithm of Floyd–Warshall was adopted. By setting target 1 as the place of departure of the search and rescue fleet, the remaining nodes are designed as targets of distress at sea (e.g., people who have fallen into the water at sea). Furthermore, it is known from previous research that the path planning research can be calculated in combination with Grey theory to obtain appropriate path planning results [6–8]. The study adopted the Floyd–GRA algorithm as the analysis method. The reason for adopting this algorithm in this study is the Floyd–Warshall algorithm is faster than other path algorithms when performing calculations. Furthermore, after quantifying the information, such as the fall into the sea, wearing life-saving equipment, and the person’s situation of injury, through Grey relational analysis (GRA), this can be combined with the distance matrix of the shortest path Floyd–Warshall algorithm. Through the information, such as the scenario of the person falling into the water, wearing a rescue suit, and the person’s injury, the model combines with the navigation distance between the rescue ship and the person in distress (targets) and whether there is a barrier during the rescue voyage. As a result, the search and rescue route at sea can be more efficient and suitable. This is the innovation of this research.

The research goal of this paper is to establish a model of optimized maritime rescue routes for the search and rescue of maritime personnel of coastal countries, and this model can assist on-site commanders in planning search and rescue routes and dispatching rescue ships. However, considering the priority of rescuing human lives at sea, the model is not involved in oil spill monitoring. This model makes it easy to obtain and observe the status of the marine distress target, immediately sorts the rescue plan by the existing rescue resources, and optimizes the search and rescue route of the rescue fleet to quickly arrive at the location of the marine distress target. Although the emergency decision-making path plan for rescuing people who have fallen into the water considered weather and sea conditions, it does not extend the aspects of early warning of oil spills at sea and pollution prevention and control. The principle of the above functions is that, in all the decisions concerning marine distress, saving human lives should be the primary consideration rather than monitoring oil spills at sea; thus, the environmental impacts caused by oil spills are not discussed in depth in this study.

The remainder of this paper comprises four sections. Section 2 reviews the literature on maritime search and rescue routes and defines the research problem as well. Section 3 outlines the detailed steps of the proposed method. Section 4 discusses the analysis results that arise from the proposed method. Section 5 presents conclusions and future applications.
2. Maritime Rescue Route and Shortest Path Algorithm Literature Review

In addition to search and rescue ships, present maritime search and rescue missions are generally operated by helicopters as a supporter [9,10]. In recent years, many scholars’ studies have shown that search and rescue work can be combined with drones to assist a person in distress [10–12]. In the part of the academic research about planning maritime search and rescue operations, Barciu [13] used risk assessment to determine the search area to enhance the effectiveness of maritime search and rescue operations. Ai et al. [14] proposed the intelligent decision-making algorithm to solve the problems of resource allocation and situation scheduling in the maritime search and rescue mission. Agbissoh OTOTE et al. [15] adopted a decision-making algorithm that is based on the optimal search theory to optimize the calculation process of the probability of containment and the probability of detection for improving the success rate of the maritime search and rescue.

Wu et al. [16] proposed the light-weight prediction-based opportunistic routing algorithm to select and prioritize the forwarding nodes. According to the research results, the trading of a 2% additional energy consumption per node for a 30% better delivery success rate was desirable. Zhang et al. [17], according to the actual situation of maritime search and rescue, improved an ant colony algorithm that is proposed for the route design. The simulation results show that the improved algorithm can be used for route design and obtain the optimal route suitable for sea search and rescue. Benz et al. [18] used semi-structured interviews with 24 experts, which provides the framework based on a literature review of the dimensions of search and rescue in the Arctic.

Cho et al. [19] proposed two phase methods for solving the coverage path planning problem of multiple heterogeneous unmanned aerial vehicles. The experimental results show that the randomized search heuristic yields are a better solution since, approximately, the optimality gap has a shorter computation time than a commercial solver. Zou et al. [20] adapted the extension cloud theory to the situation safety of two collisions, which was evaluated, and the evaluation results reflect the effectiveness of the model. Furthermore, many scholars and experts have researched and discussed the issue of the search area of maritime search and rescue [11,14,21].

The route planning of maritime search and rescue is like the vehicle routing problem (VRP) on the shore. By meeting the needs of customers (distress targets), at the same time, under certain constraints, the goals of the shortest distance, the least cost, or the least time are achieved [22,23]. Nowadays, the shortest path algorithm theories are well developed, including the Bellman–Ford algorithm, Dijkstra’s algorithm, Floyd–Warshall algorithm, Johnson algorithm, and other algorithms. However, various algorithmic theories have their advantages and disadvantages. For example: the Johnson algorithm is known for its best rescue effect, but its complex computational process is not suitable for emergencies [24]. The Dijkstra algorithm has lower computational complexity, but the analysis process cannot effectively handle cases with negative edge weights [25]. The Bellman–Ford algorithm can handle situations with negative edge weights efficiently, but its complex computational process is not suitable for emergencies [26]. Floyd–Warshall algorithms can deal with cases with negative edge weights, but the computational process is somewhat more complicated than the Dijkstra algorithm [27].

Based on the above theory of summarizing the shortest path algorithms, this study adopted the Floyd–Warshall algorithm to plan the optimal maritime search and rescue route. The Floyd–Warshall algorithm can be used to find the shortest path to either of two points under multiple targets [28,29]. In addition, the Floyd–Warshall algorithm is a dynamically programmed algorithm that can effectively process the case of positive and negative edge weights [27,30]. The Floyd–Warshall algorithm quoted in this study is no longer limited to the sea distance of the traditional Floyd–Warshall algorithm but can be measured by factors such as the fall into the sea, if the person wore life-saving equipment, and the person’s situation of injury. By setting target 1 as the place of departure of the search and rescue fleet, the remaining nodes are designed as targets of distress at sea (e.g., people who have fallen into the sea). The algorithm has a distance cost matrix on the left
and a node matrix on the right. In the distance cost matrix, it is not limited to the sea distance but can be measured in terms of personnel, ships, weather and sea conditions, and other factors. The practice is to first normalize the values of the factors to be measured individually into a de-united value between 0 and 1, and, after the standardized values of each measurement factor are summed and then multiplied by the large circle navigation distance between each node, it is brought into the distance matrix intermediate courtyard of the Floyd–Warshall algorithm.

As for the restricted areas where search and rescue units cannot enter, or if the direct route results in being indirect due to random dynamic drifting objects at sea (such as islands, sea drifts, offshore working platforms, etc.), the Floyd–Warshall algorithm can find the location of the transit point of the sea search and rescue route by setting the distance cost between the nodes to $\infty$. The search and rescue fleet transit point may be more than one, but it can make the total search and rescue route shorter and save more time regarding the total search and rescue sea voyage.

3. Research Method

The concept of method in this paper is to convert the factors in the maritime search and rescue into the search and rescue cost and calculate the shortest path in order to accelerate the completion of the search and rescue mission. From the very beginning, the shortest path situation is calculated according to the Floyd–Warshall algorithm. Afterwards, by Grey relational analysis (GRA), the weight value of search and rescue factor is calculated and converted into distance weight. Finally, based on the above analysis results, an optimized path model is constructed; on the other hand, optimized solutions of search and rescue are obtained.

3.1. Floyd–Warshall Algorithm

The main issue of the shortest path is to explore the shortest path between two target points. This problem was first developed by military strategy, whose purpose is to consider the transportation of strategic materials and tactical interception [28,31].

Robert Floyd proposed the Floyd–Warshall algorithm in 1962. It is one of the algorithms to solve the problem of shortest path besides the Dijkstra algorithm [27]. Floyd–Warshall algorithm is a type of algorithm of all pair shortest path, which finds the shortest route for all pairs of nodes that exist on a graph. This algorithm does not just explore the path between two particular nodes but creates the shortest path table between the nodes. This algorithm is not only weighted and directed graph but also calculates the negative cost [29,30]. Floyd–Warshall algorithm is one of the variants of dynamic programming, which solves the problem by searching for mutually bound solutions from inspecting other solutions. Thus, the solutions are formed by the front solutions, and more than one solution is found.

The Floyd–Warshall algorithm starts with the iteration from the first point. Then, the track or path is added by evaluating all points to the destination point. Briefly describe the calculation process of Floyd–Warshall algorithm as follows: Assuming that $G$ is represented as an $n \times n$ matrix, the weight of its side is $W = [w_{ij}]$, as shown in Equation (1).

$$W_{ij} = \begin{cases} 
0 & i = j \\
w(i,j) & i \neq j \text{ and } (i,j) \in E \\
\infty & i \neq j \text{ and } (i,j) \notin E
\end{cases} \quad (1)$$

Let $d_{ij}^{(k)}$ be the distance of the shortest path from $i$ to $j$, and all nodes on the path are set to $\{1, 2, \ldots, k\}$. Further, let $d_{ij}^{(0)}$ be $W_{ij}$; that is, there is no node; let $D^{(k)}$ be an $n \times n$ matrix $[d_{ij}^{(k)}]$. Therefore, if the shortest path $d_{ij}$ includes node $k$, the shortest path of $d_{ij}$ is composed of sub-paths $d_{ik}$ and $d_{kj}$. Each sub-path can only contain nodes between $\{1, 2, \ldots, k - 1\}$; that is, its distance is: $d_{ik}^{(k-1)}$ and $d_{kj}^{(k-1)}$. According to the aforementioned calculation
concept, $D^{(0)} = [W_{ij}]$ and the above verified $D^{(k)}$, the following Equations (2) and (3) can be obtained:

$$d^{(0)}_{ij} = \begin{cases} 0 & i = j \\ W_{ij} & i \neq j \end{cases} , i, j = \{1, 2, \ldots n\}$$  \hspace{1cm} (2)

$$d^{(k)}_{ij} = \min \{d^{(k-1)}_{ij} - d^{(k-1)}_{k}, d^{(k-1)}_{ij} + d^{(k-1)}_{k} \} , \{ k = \{1, 2, \ldots n\} \}$$  \hspace{1cm} (3)

3.2. Grey Relational Analysis

GRA is an analysis model proposed by Professor Deng in 1982. The features of GRA can perform data analysis and calculations for things such as uncertainty, multivariate input, discrete data, and data incompleteness [32–34]. GRA can project the sequence data on the geometric space by finding the correlation of one sequence to other sequences. Then, use the method of measuring the proximity of geometric shapes to solve the shortcomings of general traditional statistical regression. Briefly describe the calculation process of the GRA method as follows:

Let $X = \{x_0, x_1, x_2, \ldots, x_i\}$ be a sequence (alternative) set; $x_0$ expresses the referential alternative and $x_i$ refers to the compared alternative. Suppose $x_0$ and $x_i$ are the respective values at criterion $k$, while $k = 1, 2, \ldots, n$ for $x_0$ and $x_i$. The Grey relation coefficient $\gamma(x_0(k), x_i(k))$ of the alternatives at criterion $k$ can be obtained by Equation (4)

$$\gamma(x_0(k), x_i(k)) = \frac{\min_i \min_k \Delta_{0i}(k) + \xi \max_i \max_k \Delta_{0i}(k)}{\Delta_{0i}(k) + \xi \max_i \max_k \Delta_{0i}(k)}$$  \hspace{1cm} (4)

where $\Delta_{ij} = |x_0(k) - x_i(k)|$, $\xi$ is the distinguishing coefficient and $\xi \in [0, 1]$. $\xi$ is used to weaken the situation where the value of $\max_i \max_k \Delta_{0i}(k)$ is too large and distorted. $\xi$ will change the relative value of $\gamma(x_0(k), x_i(k))$ but does not affect the ranking of the Grey correlation degree [32–34]. As shown in Equation (5):

$$\gamma(x_0(k), x_i(k)) = \sum_{j=1}^{n} \gamma(x_0(k), x_j(k))$$  \hspace{1cm} (5)

This paper comprehensively averages the Grey correlation degree obtained by each $\xi$ value at first and calculates the weight value after obtaining the comprehensive Grey correlation sequence. As shown in Equation (6):

$$W(V)_n = \frac{G_n}{\sum G}$$  \hspace{1cm} (6)

The $(W(V))$ obtained from GRA is used as the $(W'(V))$ of the Floyd–Warshall algorithm. According to the reference, also pointed out that the Floyd–Warshall algorithm can find all the distances of each node and calculate the minimum weight of all paths [27,29,30]. Before becoming $(W'(V))$, since the original point weight value is positive, the calculation method of the Floyd–Warshall algorithm is reversed, the evaluation index needs to be normalized, and this process can set all values to $[0, 1]$. The evaluation index in the article needs to be standardized through the $Min$ index value and the $Max$ index value, as shown in Equations (7) and (8):

$$Min : \frac{Min (W(V))}{W(V)_n}$$  \hspace{1cm} (7)

$$Max : \frac{W(V)_n}{Max (W(V))}$$  \hspace{1cm} (8)
After the calculation of \((W'(V))\) is completed, it is continued to convert \((W'(V))\) to \((W(E))\). In the conversion process, the ratio of the destination to all vertices other than the departure point needs to be considered, as Equation (9) shows:

\[
W(E)_{ij} = \frac{W'(V)_j}{\sum_{k=1}^{n}W'(V)_k - W'(V)_i} 
\]  
(9)

The final weighted distance is the value obtained by considering both \((W(E))\) and distance cost \((D_{ij} * W(E)_{ij})\). In this article, the solution process of optimizing the maritime search and rescue route is presented in the form of graphic method. This study considers the shortest search and rescue route and cost to achieve the effect of optimizing the maritime search and rescue route of coastal countries. When calculating the distance weight, \((W'(V))\) (the weight of the search and rescue target) needs to be converted to \((W(E))\) (the weight of the distance between the two targets) to generate a distance weight in accordance with the actual situation.

4. Experimental Results and Analysis

The Floyd–Warshall algorithm can find all the shortest paths in the multi-source shortest path problem, which indicates that this mode can effectively allocate and find the best search and rescue route and plan [29,30]. In order to optimize the formulation of maritime search and rescue routes, the research adopts the practice to convert the distress target information into weights by using GRA. The search and rescue cost is added as a consideration in the calculation process. The search and rescue cost and distance will be the following basis of evaluation of the shortest maritime search and rescue route. Through the information of these known distress targets, the optimized maritime search and rescue route is generated, so the OSC can use the evaluation results as the consideration of the overall search and rescue dispatch. It makes OSC dispatch search and rescue fleets more accurate and allows all the targets in distress to be rescued more safely within the effective time.

This research used a simulation case to illustrate the planning of maritime search and rescue routes. In the test case of this article, the shortest path will first be used to plan the maritime search and rescue route, and then the search and rescue cost is added based on the analysis results of the shortest path to obtain the optimized maritime search and rescue route.

The simulation case in the study is set as a ship in distress at sea, and the people falling into the water are waiting for rescue while they are in the water or in a lifeboat. The target in distress represents a person in distress, and the situation of each target in distress is as follows: rescue departure target 1 is the place of departure of the search and rescue fleet. In distress target 2, the person falling into the water is wearing life-saving equipment but is seriously injured. In distress target 3, the person who is falling into the water did not wear life-saving equipment and is slightly injured. In distress target 4, the person falling into the water is wearing life-saving equipment and suffered minor injuries. In distress target 5, the person falling into the water is wearing life-saving equipment and suffered minor injuries. In distress target 6, the person in distress is not injured and is waiting for rescue on the ship in distress. The distance between the distress targets is shown as Table 1.

The value of the distance table matrix in Table 1 is the direct sea navigation distance between rescue departure target 1 and the distress targets (distress target 2 to distress target 6), but the diagonal distance value is located in the position of each target itself and is fixed to 0 (ie., distress target 2 to distress target 2, distance = 0). In the study, the value of the direct sailing distance between the two targets is calculated by the great circle sailing. For example, the value of 14.78 in Table 1 is the direct sailing distance from rescue departure target 1 to distress target 2; the value of 0.16 in the table is the direct sailing distance from distress target 3 to distress target 5, and so on.
Table 1. Distress target distance situation.

|     | 1   | 2   | 3   | 4   | 5   | 6   |
|-----|-----|-----|-----|-----|-----|-----|
| 1   | 0.00| 14.78| 17.86| 16.38| 17.21| 16.49|
| 2   | 14.78| 0.00| 0.57| 0.79| 0.86| 0.84|
| 3   | 17.86| 0.57| 0.00| 0.29| 0.16| 0.25|
| 4   | 16.38| 0.79| 0.29| 0.00| 0.14| 0.12|
| 5   | 17.21| 0.86| 0.16| 0.14| 0.00| 0.06|
| 6   | 16.49| 0.84| 0.25| 0.12| 0.06| 0.00|

Note: the unit is nautical mile.

4.1. The Shortest Maritime Search and Rescue Route

This study adopted the Floyd–Warshall algorithm to calculate the shortest path. For the distance situation of each distress target, refer to Table 1. This research provides examples of data and how they are used, as shown in Appendix A. In Appendix A, this study explains the calculation process graphically, as shown in Tables A1–A6. The results after analysis and calculation are shown in Table 2.

Table 2. Floyd–Warshall algorithm calculation matrix.

| Vertex | 1  | 2  | 3  | 4  | 5  | 6  | 1  | 2  | 3  | 4  | 5  | 6  |
|--------|----|----|----|----|----|----|----|----|----|----|----|----|
| 1      | 0.00| 14.78| **15.35**| **15.57**| **15.51**| **15.57**| 1   | 2   | 3   | 4   | 5   | 6   |
| 2      | 14.78| 0.00| 0.57| 0.79| **0.73**| **0.79**| 2   | 1   | 2   | 3   | 4   | 3   |
| 3      | **15.35**| 0.57| 0.00| 0.29| 0.16| **0.22**| 3   | 2   | 2   | 3   | 4   | 5   |
| 4      | **15.57**| 0.79| 0.29| 0.00| 0.14| 0.12| 4   | 2   | 2   | 3   | 4   | 5   |
| 5      | **15.51**| **0.73**| 0.16| 0.14| 0.00| 0.06| 5   | 3   | 3   | 3   | 4   | 5   |
| 6      | **15.57**| 0.79| **0.22**| 0.12| 0.06| 0.00| 6   | 5   | 5   | 5   | 4   | 5   |

In the study, the two matrix values presented in Table 2 are brought into the initial matrix data of the Floyd–Warshall algorithm matrix calculus according to the values of Table 1, where the left matrix is the distance matrix (brought in by Table 1) and the right matrix is the node matrix (adopted to cooperate with the calculation of whether the node route of the optimal search and rescue route is directly sailing or it needs to be navigated around other targets).

According to the results of the Floyd–Warshall algorithm analysis, the shortest maritime search and rescue route and the navigation distance of search and rescue ships are shown in Table 3 below.

Table 3. Floyd–Warshall algorithm shortest search and rescue route results.

| Shortest Search and Rescue Route | Search and Rescue Ship Sailing Distance |
|---------------------------------|----------------------------------------|
| 1→2→3                          | 15.35                                  |
| 1→2→4                          | 15.57                                  |
| 1→3→5                          | 15.51                                  |
| 1→5→6                          | 15.57                                  |
| 2→3→5                          | 0.73                                   |
| 2→5→6                          | 0.79                                   |
| 3→5→6                          | 0.22                                   |
The results of finding the shortest search and rescue route by using the Floyd–Warshall algorithm show that, during the maritime search and rescue process, two ships need to be assigned to search and rescue. One ship departs from rescue departure target 1, passing by distress target 2, and finally reaches distress target 4. It sails 15.57 nautical miles. Another ship departs from rescue departure target 1, passing by distress target 2, distress target 3, and distress target 5, and finally reaches distress target 6, sailing 15.57 nautical miles. In the case of completing maritime search and rescue missions, the shortest rescue distance can be obtained.

4.2. Optimized Maritime Search and Rescue Route

In this study, three factors, including the situation of people in distress wearing life-saving equipment, the situation of injury, and whether they fell into the water, will be used for the evaluation indicators of search and rescue costs. The purpose is that, at the moment of a shipwreck, these three evaluation indicators are the information of persons in distress at sea that can be immediately known or directly observed.

To evaluate the weight value corresponding to the search and rescue, this study assumes several weight values. In the case of people in distress wearing life-saving equipment or not, the weight values are set to 3 for those not wearing it, 2 for one who is wearing, and 1 for one who is in the boat in distress. In the case of people falling into water or not, the weight values are set to 2 for one who is falling and 1 for one who is not falling. In the case of severity of people’s injury, the weight values are set to 3 for one who is seriously injured, 2 for one who is slightly injured, and 1 for one who is not injured. By quantifying and sorting, the result of the matrix is shown in Table 4. The GRA analyses calculated according to the results are shown in Table 5. In the study, the results in Table 5 were also drawn into Figure 1 for presentation. In this way, errors of the GRA calculation results can be checked.

| Distress Target | Evaluation Index |
|-----------------|------------------|
|                 | Life-Saving Equipment | Fell into the Sea | Situation of Injury |
| 2               | 2 | 2 | 3 |
| 3               | 3 | 2 | 2 |
| 4               | 2 | 2 | 2 |
| 5               | 2 | 2 | 2 |
| 6               | 1 | 1 | 1 |

Table 4. Arrangement of Grey correlation matrix of marine distress situation.

| Distress Target | Distinguishing Coefficient (ξ) | Grey Correlation Degree | GREY Relational Ordinal | Weight |
|-----------------|--------------------------------|-------------------------|-------------------------|--------|
| 2               | 0.722 0.762 0.792 0.815 | 0.833 0.848 0.861 0.872 | 0.881 0.889 0.828 | 1      | 0.067 |
| 3               | 0.167 0.286 0.375 0.444 | 0.500 0.545 0.583 | 0.615 0.643 0.667 | 0.483 | 3      | 0.200 |
| 4               | 0.141 0.246 0.327 0.392 | 0.444 0.489 0.526 | 0.586 0.611 0.432 | 4      | 0.267 |
| 5               | 0.444 0.524 0.583 0.630 | 0.667 0.697 0.722 | 0.744 0.762 0.778 | 0.655 | 2      | 0.133 |
| 6               | 0.091 0.167 0.231 0.286 | 0.333 0.375 0.412 | 0.444 0.474 0.500 | 0.331 | 5      | 0.333 |

Table 5. GRA analysis and calculation.
According to the results in Table 5 and Figure 1, the GRA calculation results are significant. The last step is to calculate the weighted distance of the distress target through Equations (7)–(9) in this article to obtain the GRA analysis results. Then, start calculating \( W'(V) \) and \( W'(E) \). The results are shown in Table 6. This research provides examples of data and how they are used, as shown in Appendix B. In Appendix B, this study explains the calculation process, as shown in Tables A7–A9.

Table 6. Weighted distance sorting of distress targets.

|    | 1   | 2   | 3   | 4   | 5   | 6   |
|----|-----|-----|-----|-----|-----|-----|
| 1  | 0.00| 14.78| 5.95| 4.10| 8.61| 3.30|
| 2  | 14.78| 0.00| 0.09| 0.09| 0.21| 0.08|
| 3  | 5.95| 0.27| 0.00| 0.07| 0.07| 0.05|
| 4  | 4.10| 0.45| 0.06| 0.00| 0.04| 0.01|
| 5  | 8.61| 0.47| 0.03| 0.02| 0.00| 0.01|
| 6  | 3.30| 0.53| 0.05| 0.02| 0.02| 0.00|

After obtaining the weighted distance, this study uses the Floyd–Warshall algorithm again to calculate. This research provides examples of data and how they are used, as shown in Appendix C. In Appendix C, this study explains the calculation presented graphically, as shown in Tables A10–A15. The results by analysis and calculation are shown in Table 7. The Example Calculation is attached in Table S1 in the Supplemental Material available online.

Regarding the results of the analysis, the optimized maritime search and rescue route and navigation distance are shown in Table 8 below.
According to the results compiled in Table 8, the best situation for maritime search and rescue is to assign two search and rescue ships. A ship departs from rescue departure target 1, passing by distress target 6, and finally reaches distress target 4. The weighted distance of the ship is 3.32, and the navigation distance of the search and rescue ship is 16.61 nautical miles. The other ship departs from rescue departure target 1, passing by distress target 6, distress target 5, and distress target 3, and finally reaches distress target 2. The navigation distance of this ship is 3.62, and the navigation distance of the search and rescue ship is 17.28 nautical miles.

5. Discussion and Conclusions

In conducting maritime search and rescue tasks, a traditional maritime search and rescue plan needs a great deal of time for collecting information regarding falling water events. However, in order to minimize the harm of people in distress, the process of search and rescue at sea must be as short as possible. The optimized maritime search and rescue route established in this study can balance both the criticality of the distress target and the distance cost. The simulation results show that the proposed modeling method is an effective plan for maritime search and rescue routes.
This paper has built a set of maritime search and rescue route models for coastal countries, which are suitable for the on-scene commander planning search and rescue routes and dispatching rescue ships. The model based on the observable state of the distress targets sequences the rescue plan and optimizes the marine search and rescue route. When the search and rescue center receives the status of the target in distress, including the location and distance of the person who fell into the sea, the optimized planning of the maritime search and rescue route developed by this research can provide suggestions for the search and rescue operations. If the search and rescue center obtained only the distance of the target in distress, it could still dispatch the fastest search and rescue ship in the task through this shortest path mode.

Not every maritime distress incident must immediately dispatch a great deal of manpower and equipment. Aside from the factor of limited search and rescue resources, it is important to avoid depleting all the rescue resources on a single case, with the result being that there are not enough to be transferred to other distressed areas when receiving word of other simultaneous incidents. In the distance matrix of the Floyd–Warshall algorithm, the optimization model of this study introduces a concept similar to the classification guidance of marine injury inspection. This can help the maritime search and rescue commander to dispatch a high-precision rescue fleet to participate in the falling water incident. At the same time, it can also reduce the waste of search and rescue resources and the situation of insufficient rescue energy.

In addition, the current maritime search and rescue system does not have a set of global universal maritime injury classification guidelines, which is not as complete as the emergency medical examination system of the land hospital. This study can assist in planning maritime search and rescue routes in time-critical situations. This route can reasonably allocate the fleet resources required by the search and rescue route. This avoids resource shortages and delays of search and rescue at sea. In terms of future research, the evaluation method of vital signs can be adopted. By introducing the concept of vital signs of casualties on land, the accuracy of the assessment of the injuries of those who have fallen into the sea would be improved. In this way, it can increase the chance of rescue of persons in distress at sea.

The research goal of this paper is to establish a model of optimized maritime rescue routes for the search and rescue of maritime personnel of coastal countries, and this model can assist on-site commanders in planning search and rescue routes and dispatching rescue ships. Although the emergency decision-making path plan for rescuing people who have fallen into the water considered weather and sea conditions, it does not extend to the aspects of early warning of oil spills at sea and pollution prevention and control. Some topics for future study include, for example, adjusting the search and rescue route by adding the oil spill monitoring model. In addition, it will be an interesting topic regarding comparing the efficiency between search and rescue ships and search and rescue helicopters.

Supplementary Materials: The following supporting information can be downloaded at: [https://www.mdpi.com/article/10.3390/jmse10040460/s1](https://www.mdpi.com/article/10.3390/jmse10040460/s1), Table S1. Example Calculation.

Author Contributions: W.-C.H. contributed to the conception of the work (writing, data collection), analyzed the data, and interpreted the results. J.-H.S. contributed to the conception and design of the work (literature search, data collection). C.-P.L. designed, drafted, and revised the work. Y.-W.C. contributed to the conception and design of the work (study design, data interpretation). All authors have read and agreed to the published version of the manuscript.

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Appendix A

The calculation processes presented graphically are shown in Tables A1–A6. These data sources come from Table 1.
Table A1. The step 1 graphical process of Floyd–Warshall algorithm.

| Step 1 | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 14.78| 17.86| 16.38| 17.21| 16.49|
| 2      | 14.78| 0.00| 0.57| 0.79| 0.86| 0.84|
| 3      | 17.86| 0.57| 0.00| 0.29| 0.16| 0.25|
| 4      | 16.38| 0.79| 0.29| 0.00| 0.14| 0.12|
| 5      | 17.21| 0.86| 0.16| 0.14| 0.00| 0.06|
| 6      | 16.49| 0.84| 0.25| 0.12| 0.06| 0.00|

Table A2. The step 2 graphical process of Floyd–Warshall algorithm.

| Step 2 | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 14.78| 15.35| 15.57| 15.64| 15.62|
| 2      | 14.78| 0.00| 0.57| 0.79| 0.86| 0.84|
| 3      | 15.35| 0.57| 0.00| 0.29| 0.16| 0.25|
| 4      | 15.57| 0.79| 0.29| 0.00| 0.14| 0.12|
| 5      | 15.64| 0.86| 0.16| 0.14| 0.00| 0.06|
| 6      | 15.62| 0.84| 0.25| 0.12| 0.06| 0.00|

Table A3. The step 3 graphical process of Floyd–Warshall algorithm.

| Step 3 | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 14.78| 15.35| 15.57| 15.60| 15.51|
| 2      | 14.78| 0.00| 0.57| 0.79| 0.82| 0.82|
| 3      | 15.35| 0.57| 0.00| 0.29| 0.16| 0.25|
| 4      | 15.57| 0.79| 0.29| 0.00| 0.14| 0.12|
| 5      | 15.60| 0.82| 0.16| 0.14| 0.00| 0.06|
| 6      | 15.60| 0.82| 0.25| 0.12| 0.06| 0.00|

Table A4. The step 4 graphical process of Floyd–Warshall algorithm.

| Step 4 | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 14.78| 15.35| 15.57| 15.60| 15.57|
| 2      | 14.78| 0.00| 0.57| 0.79| 0.82| 0.82|
| 3      | 15.35| 0.57| 0.00| 0.29| 0.16| 0.25|
| 4      | 15.57| 0.79| 0.29| 0.00| 0.14| 0.12|
| 5      | 15.51| 0.73| 0.16| 0.14| 0.00| 0.06|
| 6      | 15.60| 0.82| 0.25| 0.12| 0.06| 0.00|

Table A5. The step 5 graphical process of Floyd–Warshall algorithm.

| Step 5 | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 14.78| 15.35| 15.57| 15.57| 15.57|
| 2      | 14.78| 0.00| 0.57| 0.79| 0.79| 0.79|
| 3      | 15.35| 0.57| 0.00| 0.29| 0.16| 0.22|
| 4      | 15.57| 0.79| 0.29| 0.00| 0.14| 0.12|
| 5      | 15.51| 0.73| 0.16| 0.14| 0.00| 0.06|
| 6      | 15.57| 0.79| 0.22| 0.12| 0.06| 0.00|
Table A6. The step 6 graphical process of Floyd–Warshall algorithm.

| Vertex | 1    | 2    | 3    | 4    | 5    | 6    |
|--------|------|------|------|------|------|------|
| 1      | 0.00 | 14.78| 15.35| 15.57| 15.51| 15.57|
| 2      | 14.78| 0.00 | 0.57 | 0.79 | 0.73 | 0.79 |
| 3      | 15.35| 0.57 | 0.00 | 0.29 | 0.16 | 0.22 |
| 4      | 15.57| 0.79 | 0.29 | 0.00 | 0.14 | 0.12 |
| 5      | 15.51| 0.73 | 0.16 | 0.14 | 0.00 | 0.06 |
| 6      | 15.57| 0.79 | 0.22 | 0.12 | 0.06 | 0.00 |

Appendix B

The calculation processes of \((W'(V))\) and \((W(E))\) are shown in Tables A7–A9.

Table A7. Minimum revise table.

| Distress Target | Grey Relational Ordinal | W | Revise W |
|----------------|-------------------------|---|----------|
| 1              | NIL.                    | 0.00 | 0.00    |
| 2              | 1                       | 0.07 | 1.00    |
| 3              | 3                       | 0.20 | 0.33    |
| 4              | 4                       | 0.27 | 0.25    |
| 5              | 2                       | 0.13 | 0.50    |
| 6              | 5                       | 0.33 | 0.20    |

Table A8. \((W'(V))\) table.

|       | 1    | 2    | 3    | 4    | 5    | 6    |
|-------|------|------|------|------|------|------|
| 1     | 0.00 | 1.00 | 0.33 | 0.25 | 0.50 | 0.20 |
| 2     | 1.00 | 0.00 | 0.16 | 0.12 | 0.24 | 0.10 |
| 3     | 0.33 | 0.48 | 0.00 | 0.23 | 0.46 | 0.18 |
| 4     | 0.25 | 0.57 | 0.19 | 0.00 | 0.29 | 0.11 |
| 5     | 0.50 | 0.55 | 0.18 | 0.14 | 0.00 | 0.11 |
| 6     | 0.20 | 0.63 | 0.21 | 0.16 | 0.32 | 0.00 |

Table A9. \((W(E))\) table.

|       | 1    | 2    | 3    | 4    | 5    | 6    |
|-------|------|------|------|------|------|------|
| 1     | 0.00 | 14.78| 5.95 | 4.10 | 8.61 | 3.30 |
| 2     | 14.78| 0.00 | 0.57 | 0.79 | 0.86 | 0.84 |
| 3     | 17.86| 0.57 | 0.00 | 0.29 | 0.16 | 0.25 |
| 4     | 16.38| 0.79 | 0.29 | 0.00 | 0.14 | 0.12 |
| 5     | 17.21| 0.86 | 0.16 | 0.14 | 0.00 | 0.06 |
| 6     | 16.49| 0.84 | 0.25 | 0.12 | 0.06 | 0.00 |

Appendix C

The calculation processes presented graphically are shown in Tables A10–A15. These data sources come from Table 6.
### Table A10. The step 1 graphical process of the best search and rescue route.

| Vertex | 1   | 2   | 3   | 4   | 5   | 6   | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 14.78| 5.95| 4.10| 8.61| 3.30| 1   | 2   | 3   | 4   | 5   | 6   |
| 2      | 14.78| 0.00| 0.09| 0.09| 0.21| 0.08| 2   | 1   | 2   | 3   | 4   | 5   | 6   |
| 3      | 5.95| 0.27| 0.00| 0.07| 0.07| 0.05| 3   | 1   | 2   | 3   | 4   | 5   | 6   |
| 4      | 4.10| 0.45| 0.06| 0.00| 0.04| 0.01| 4   | 1   | 2   | 3   | 4   | 5   | 6   |
| 5      | 8.61| 0.47| 0.03| 0.02| 0.00| 0.01| 5   | 1   | 2   | 3   | 4   | 5   | 6   |
| 6      | 3.30| 0.53| 0.05| 0.02| 0.02| 0.00| 6   | 1   | 2   | 3   | 4   | 5   | 6   |

### Table A11. The step 2 graphical process of the best search and rescue route.

| Vertex | 1   | 2   | 3   | 4   | 5   | 6   | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 14.78| 5.95| 4.10| 8.61| 3.30| 1   | 2   | 3   | 4   | 5   | 6   |
| 2      | 14.78| 0.00| 0.09| 0.09| 0.21| 0.08| 2   | 1   | 2   | 3   | 4   | 5   | 6   |
| 3      | 5.95| 0.27| 0.00| 0.07| 0.07| 0.05| 3   | 1   | 2   | 3   | 4   | 5   | 6   |
| 4      | 4.10| 0.45| 0.06| 0.00| 0.04| 0.01| 4   | 1   | 2   | 3   | 4   | 5   | 6   |
| 5      | 8.61| 0.47| 0.03| 0.02| 0.00| 0.01| 5   | 1   | 2   | 3   | 4   | 5   | 6   |
| 6      | 3.30| 0.53| 0.05| 0.02| 0.02| 0.00| 6   | 1   | 2   | 3   | 4   | 5   | 6   |

### Table A12. The step 3 graphical process of the best search and rescue route.

| Vertex | 1   | 2   | 3   | 4   | 5   | 6   | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 6.23| 5.95| 4.10| 6.02| 3.30| 1   | 3   | 3   | 4   | 3   | 6   |
| 2      | 6.04| 0.00| 0.09| 0.09| 0.16| 0.08| 2   | 3   | 4   | 5   | 6   |
| 3      | 5.95| 0.27| 0.00| 0.07| 0.07| 0.05| 3   | 1   | 2   | 3   | 4   | 5   |
| 4      | 4.10| 0.33| 0.06| 0.00| 0.04| 0.01| 4   | 1   | 3   | 4   | 5   | 6   |
| 5      | 5.98| 0.30| 0.03| 0.02| 0.00| 0.01| 5   | 3   | 3   | 4   | 5   | 6   |
| 6      | 3.30| 0.33| 0.05| 0.02| 0.02| 0.00| 6   | 1   | 3   | 4   | 5   | 6   |

### Table A13. The step 4 graphical process of the best search and rescue route.

| Vertex | 1   | 2   | 3   | 4   | 5   | 6   | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 4.43| 4.16| 4.10| 4.14| 3.30| 1   | 4   | 4   | 4   | 4   | 6   |
| 2      | 4.19| 0.00| 0.09| 0.09| 0.13| 0.08| 2   | 4   | 2   | 3   | 4   | 4   |
| 3      | 4.17| 0.27| 0.00| 0.07| 0.07| 0.05| 3   | 4   | 2   | 3   | 4   | 5   |
| 4      | 4.10| 0.33| 0.06| 0.00| 0.04| 0.01| 4   | 4   | 3   | 3   | 4   | 5   |
| 5      | 4.12| 0.30| 0.03| 0.02| 0.00| 0.01| 5   | 4   | 3   | 3   | 4   | 5   |
| 6      | 3.30| 0.33| 0.05| 0.02| 0.02| 0.00| 6   | 1   | 3   | 3   | 4   | 5   |

### Table A14. The step 5 graphical process of the best search and rescue route.

| Vertex | 1   | 2   | 3   | 4   | 5   | 6   | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 4.43| 4.16| 4.10| 4.14| 3.30| 1   | 4   | 4   | 4   | 4   | 6   |
| 2      | 4.19| 0.00| 0.09| 0.09| 0.13| 0.08| 2   | 4   | 2   | 3   | 4   | 4   |
| 3      | 4.17| 0.27| 0.00| 0.07| 0.07| 0.05| 3   | 4   | 2   | 3   | 4   | 5   |
| 4      | 4.10| 0.33| 0.06| 0.00| 0.04| 0.01| 4   | 4   | 3   | 3   | 4   | 5   |
| 5      | 4.12| 0.30| 0.03| 0.02| 0.00| 0.01| 5   | 4   | 3   | 3   | 4   | 5   |
| 6      | 3.30| 0.33| 0.05| 0.02| 0.02| 0.00| 6   | 1   | 3   | 3   | 4   | 5   |
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**Table A15.** The step 6 graphical process of the best search and rescue route.

| Vertex | 1   | 2   | 3   | 4   | 5   | 6   |
|--------|-----|-----|-----|-----|-----|-----|
| 1      | 0.00| 3.62| 3.35| 3.32| 3.32| 3.30|
| 2      | 3.38| 0.00| 0.09| 0.09| 0.10| 0.08|
| 3      | 3.25| 0.27| 0.00| 0.07| 0.07| 0.05|
| 4      | 3.31| 0.33| 0.06| 0.00| 0.03| 0.01|
| 5      | 3.31| 0.30| 0.03| 0.02| 0.02| 0.01|
| 6      | 3.30| 0.32| 0.05| 0.02| 0.02| 0.00|
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