

Deep-Sea Rescue: Localization and Search Strategies in Challenging Oceanic Environments

Summary

The Greek Maritime Cruise Mini-Submersible Company (MCMS) aims to develop a safety program to predict the location of the submersible in case of failure. The research involves the establishment of a localization model that considers the changes in the physical environment of the submersible in the situation of communication loss or propulsion loss, including factors such as fluid resistance, ocean currents and water density. We propose an integrated model based on physical analysis, probability theory and random walk to predict the location of the submersible and provide guidance for rescue operations.

For *Task 1*, predict the location of the submersible, which is influenced by several factors. The study begins by analyzing the locational changes of the submersible in the event of a shipwreck, including changes in acceleration due to fluid friction. A decay model is constructed to simulate the decay of the initial velocity, and a *Random Walk* model is leveraged to predict the drift path of the submersible in conjunction with real-time ocean current velocity. The uncertainty of the predicted path is reduced by a *Savitzky-Golay Filter*, and the validity of the model is verified based on the *Monte Carlo* method.

For *Task 2*, combine the *Analytic Hierarchy Process* and a *Large Language Model* to propose an evaluation framework for selecting optimal equipment for the host ship and the rescue ship. The framework considers equipment costs of the availability, the maintenance, the readiness, the usage and the utilization efficiency. By adding the ability to employ the GoogleWebSearch API for the Open AI GPT-4 model, we perform the online fact-checking and scoring of the candidate equipment to ensure the objectivity of the scores. Finally, we choose *ROV Hydroid Remus 6000* and *LR7* as the probing equipment and the rescue equipment, respectively.

For *Task 3*, we propose a search model based on the *Long Baseline Communication System* and the *Bayesian Search* for searching within the range determined by the location prediction model. These models are constructed and implemented with a combination of *Model Predictive Control* strategies to optimize search paths and reduce search time. In simulations, the probability of being able to search in about 12 hours can be more than 90%.

For *Task 4*, we consider the scalability of the model and find that it can be easily extended to other oceans. Moreover, the flexibility of the model is demonstrated by the argument that when there are multiple submersibles in the vicinity of the same ocean area, the remaining submersibles can be used as ROVs for exploration.

Finally, a sensitivity analysis on the proposed model is performed to test the robustness under different parameters. The strength of the model lies in its high scalability to adapt to search and rescue missions in different ocean areas.

Keywords: analytic hierarchy process; Bayesian search; GPT-4 as reviewers; model predictive control; random walk; Savitzky-Golay filter

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1 Introduction

1.1 Background

The Ionian Sea is the deepest part of the Mediterranean Sea, comprised of several trenches and plateaus that exceed 4500 m depth. The Maritime Cruises Mini-submersibles (MCMS) intends to use its own submersibles for an underwater exploration project. The company now needs to develop safety procedures and obtain regulatory approval. The safety procedures require the development of a model to predict the location of the submersible in the event of a failure. One such failure could be a loss of contact with the main vessel or a mechanical failure resulting in a loss of energy.

In the case of submersible searches, the submersible will simply sink to the bottom of the ocean or at some point of neutral buoyancy underwater. These two basic scenarios are shown in Fig. 1. Additionally, the ocean currents, the density of the water, and the topography of the seabed in the waters in which they are located need to be taken into account.

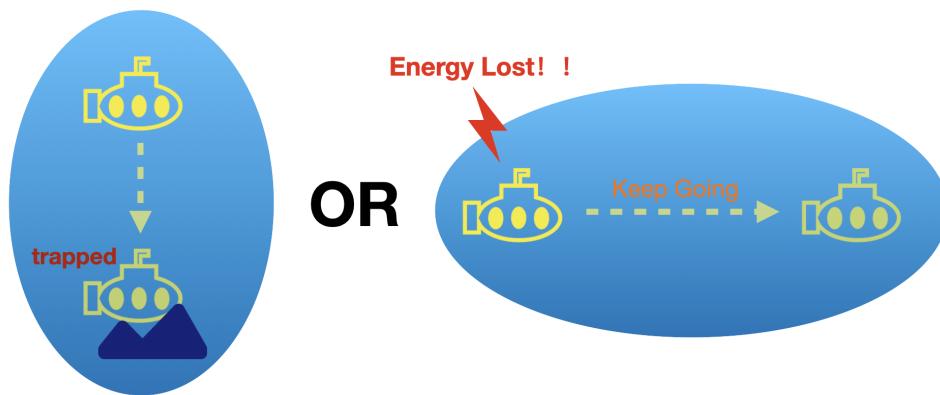


Figure 1: Possible Scenarios after a Malfunction

1.2 Problem Restatement and Analysis

- Problem one: A localization model predicts the location of a submersible over time. Consideration needs to be given to what equipment can be carried and what messages can be sent to reduce model uncertainty.
- Problem two: An equipment carrying program designed for the host ship. Consideration needs to be given to the costs of different equipment and its functionality.
- Problem three: A model sets up an initial point of search and a search scheme based on the localization model . It is required to find the minimum time to search and determine the probability of finding the submersible.
- Problem four: Extend the model to other marine areas, it is also necessary to consider the situation involving multiple submersibles.
- Memorandum: A two-page memorandum addressed to the Greek government. A detailed plan needs to be provided in it to try to win approval for this project.

1.3 Overview

To avoid complicated description , intuitively reflect our work process, the flow chart is shown as the following figure:

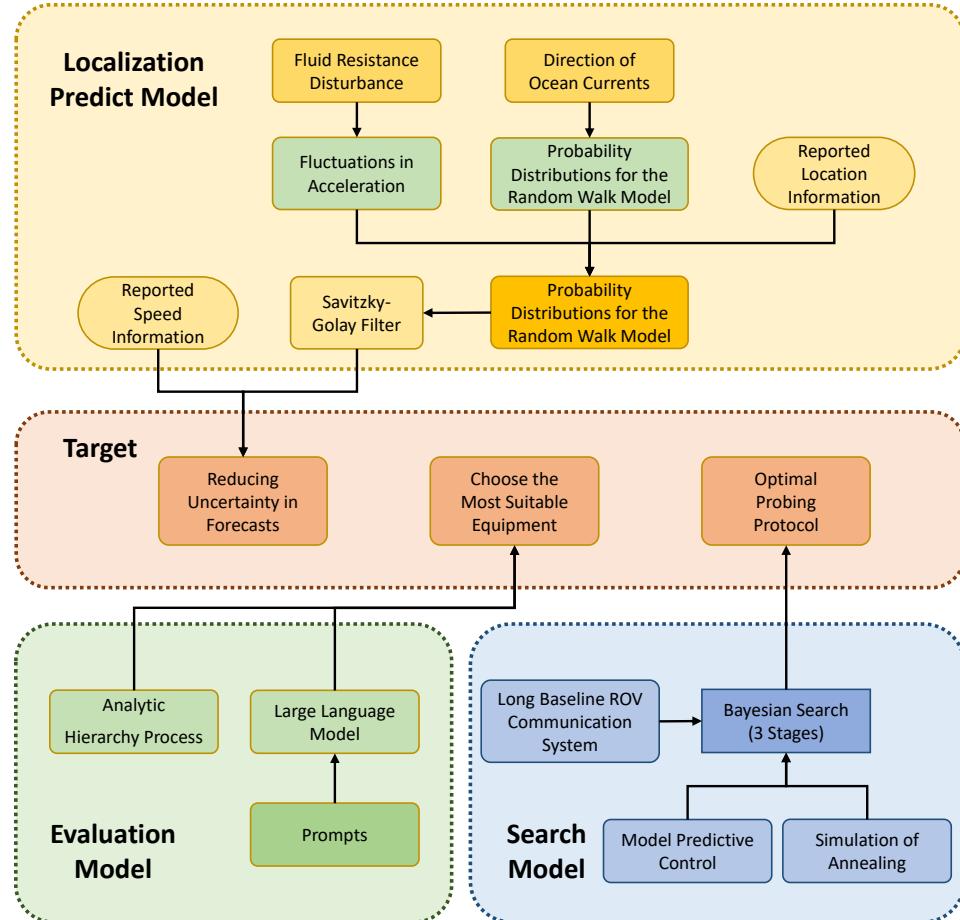


Figure 2: Workflow Diagram for Targeting and Search Strategies

1.4 Dataset

We look up the current data for the Ionian Sea on website^[1], including direction and current speed. The data on the website is updated once every five days, and here we utilize the ocean current data from February 4th. Furthermore, we refer to the data of Ionian ocean currents in past research papers^[2] and from the Physics Production Unit (PU) at the National Institute of Geophysics and Volcanology (INGV).^[3]

2 Assumptions

1. It is assumed that the movement of a submersible is only affected by the direction of the ocean currents, and the density of the sea water and obstacles on the seabed.

2. It is assumed that the submersible will not sink during its motion at the point of neutral buoyancy after losing propulsion.
3. It is assumed that the search equipment signal remains normal while searching for the submersible.
4. It is assumed that the failure of the submersible means that the communications as well as the propulsion are all damaged. Since communications are available to determine its exact location and propulsion is available to float to the surface and use radio to communicate.

3 List of Notation

Table 1: Notations Table

Symbols	Descriptions
V	the velocity of submersible
D	combined displacement of the submersible
D_V	displacement due to the initial velocity of the submersible
D_{Sea}	displacement due to oceanographic factors
α	direction of submersible displacement
β	direction of initial velocity of the submersible
θ	direction of ocean current speed
ϕ	direction of random disturbance of sea water
ρ	water density
σ_k	sea state coefficients
γ	marine terrain index
t_{wre}	actual time of wreck
x_k^t	state vector of the target at moment k
z_k^s	state vector of the search equipment at moment k

4 Submersible Location Prediction Model

We develop a model to predict the trajectory of a wrecked submersible by combining the physical analysis and the simulations of the Ionian Sea currents, facilitating probe and rescue operations by the main and rescue vessels. Regarding the proposed model, we analyze its uncertainties and offer the communication recommendations between the submersible and the host ship to reduce these uncertainties.

4.1 Physical Background

In this section, we discuss the physical background required for model construction. The wrecked submersible's location in the ocean are subject to changes due to various factors in the marine environment. Differences in speed lead to variations in fluid resistance, resulting in changes in acceleration. The physical environment

is depicted based on the fluid resistance received and the state equation of seawater. When the submersible experiences a loss of propulsion, fluid resistance directly impacts its location, making resistance modeling key to predicting the submersible's location. Fluid resistance of the submersible underwater is determined by hydrodynamic theory, denoted as

$$R = R_F + R_S + R_W + R_{AP} \quad (1)$$

where R_F , R_S , R_W and R_{AP} denote the friction resistance, the shape resistance, the wave resistance, and the appendage resistance, respectively. Note that due to the submersible's deep dive depth, the wave resistance is approximately zero. The submersible's appendage resistance is also zero because there exists no appendages attached to it. Therefore, we only need to consider the friction resistance and shape resistance of the submersible.^[4]

The shape resistance of a submersible can be expressed as:

$$R_S = \frac{1}{2}\rho V^2 S C_E \quad (2)$$

where C_E is the shape resistance coefficient related to the shape of the submersible, taking the value of 0.05 here. The friction resistance can be expressed as:

$$R_F = \frac{1}{2}\rho V^2 S (C_F + \Delta C_F) \quad (3)$$

where C_F and ΔC_F are the coefficients of frictional resistance, ΔC_F is the roughness allowance coefficient independent of the Reynolds number whose value is taken as 0.0004. The coefficient C_F can be expressed as:

$$\begin{cases} C_F = \frac{0.075}{(\lg R_e - 2)^3} \\ R_e = \frac{VL}{v} \end{cases} \quad (4)$$

where R_e is a Reynolds number and denotes the ratio of the inertial forces viscous forces in fluid mechanics, V and L represent the speed and the length of the submersible, respectively. v denotes the coefficient of water motion viscosity, which can be represented by the coefficient of dynamic viscosity μ :

$$\begin{cases} v = \frac{\mu}{\rho} \\ \mu = R \frac{dn}{dV_f} \end{cases} \quad (5)$$

It can be obtained that v is a function of the density, i.e., $v = f(\rho)$. We can finally get

$$\begin{cases} R = \frac{1}{2}\rho V^2 S (C_F + \Delta C_F + C_E) \\ a = \frac{1}{2M}\rho V^2 S (C_F + \Delta C_F + C_E) \end{cases} \quad (6)$$

where a is the acceleration, C_F is the only variable and is related to the density of seawater ρ and M denotes the mass of the submersible.

The density of seawater affects both the fluid resistance and the depth location of the submersible, because the submersible has a tendency to keep its own depth

location in the neutral buoyancy point during the movement process. The density of seawater directly determines the location of the neutral buoyancy point. Reviewing the existing literature, we find that the density of seawater is mainly affected by three factors: salinity, temperature, pressure. Thus, we have the following equation:

$$\rho = \mathcal{P}(S_a, T, P) \quad (7)$$

S_a as the salinity, T as the temperature, P as the pressure. Based on the literature, for many theoretical and modeling purposes in oceanography, it is convenient to consider the density as a 25-term expression. However, this is still challenging for our modeling task. Thus, considering the large number of factors affecting seawater salinity, temperature and pressure and the complexity of the relationship, we assume that the three seawater parameters mentioned above obey a certain distribution, the expectation and variance of which are determined by the specific local environment of the ocean area. Therefore, we introduce a seawater factor coefficient σ_k to characterize the influence of seawater parameters by factors such as ocean topography.

4.2 Predictive Model Establishment

In this section, considering the speed of the submersible at the time of the wreck and the earliest ocean conditions, we establish a model to predict the location of the wrecked submersible. We consider that the displacement of the submersible is affected by its own initial state and seawater factors, which can be expressed as:

$$D = D_V + D_{Sea} \quad (8)$$

4.2.1 Decaying Model of Initial Velocity

According to the actual situation, the submersible transmits the information at a certain frequency in normal operation. When the submersible is wrecked, the host ship can not determine the exact time of the wreck of the submersible and other real data, including the actual location coordinates, the actual speed, etc. It can only speculate based on the last transmitted information. Therefore, the actual time of the wreck, the authentic speed, and other variables obey a certain distribution as random variables.

We assume that the actual time of the crash t_{wre} obeys a uniform distribution of $[0, T]$. The authentic speed obeys a truncated normal distribution. The mean of this distribution is the speed information from the last transmitted message, and the variance is based on a formula related to the true event of the collision t_{wre} . The formula ensures that the larger the actual time of the collision t_{wre} , the greater the variance.

The construction of the variance equation takes into account the introduction of Sea state coefficient σ_k , to characterize the degree of dispersion in the variation of seawater parameters due to environmental factors such as ocean topography. The construction of the variance formula takes into account the introduction of sea-factor random coefficients, which are distributed as follows:

$$\begin{cases} t_{wre} \sim \mathcal{U}(0, T) \\ V' \sim \mathcal{N}_{tr} (V, \frac{1}{3T}t_{wre}(V_{max} - V), 0, V_{max}) \\ \beta' \sim \mathcal{N}_{tr} (\beta, \frac{1}{3T}t_{wre}\pi, \beta - \pi, \beta + \pi) \end{cases} \quad (9)$$

After randomly assigning values to the aforementioned random variables, thus determining the actual data information, we further consider the impact of fluid resistance on the initial velocity, thereby analyzing the random displacement generated by the initial velocity.

$$\begin{cases} a_x = a \cos \alpha \\ a_y = a \sin \alpha \\ a_\beta = a_x \cos \beta + a_y \sin \beta \end{cases} \quad (10)$$

where a_x and a_y are the components of the acceleration in the x and y directions, respectively. a_β is the component of the acceleration in the direction of the initial velocity.

We split the continuous motion process into discrete processes with equal time intervals, and the motion state of the submersible is a uniformly accelerated linear motion in one unit time dt , the displacement due to the initial velocity of the submersible can be expressed as:

$$dD_V = V dt + \frac{1}{2} a_\beta dt^2 \quad (11)$$

4.2.2 Random Walk Model

Considering the impact of the initial speed on predicting location, we need to analyze the displacement produced by the submersible in a dynamic environment. Therefore, we incorporate the influence of real ocean currents into the random walk model to simulate the submersible's drift path.

According to the random walk model, with no disturbances, an object's potential motion angle in a plane ranges from 0 to 2π , with each angle having an equal probability. Now, considering disturbances from random movements of ocean currents, the submersible's motion angle changes with a certain probability. We use a truncated normal distribution to represent the probability distribution. The mean angle μ_N of the distribution is equal to the angle in the direction of the current flow. According to the *Pauta Criteria*, wanting to achieve essentially full coverage of $0 \sim \pi$, we set σ equal to $\pi/3$. Thus, it can be expressed as:

$$\phi \sim \mathcal{N}_{tr} \left(\theta, \frac{\pi}{3}, \theta - \pi, \theta + \pi \right) \quad (12)$$

Therefore, the random displacements caused by multifaceted oceanic factors such as currents can be summarized in the following equation:

$$\begin{cases} dD_{Sea_x} = u \cos \phi dt \\ dD_{Sea_y} = u \sin \phi dt \end{cases} \quad (13)$$

Next, we construct the ocean current vector. Here is a map of the ocean currents distribution in the Ionian Sea, as shown in Fig. 3. We can clearly see that there are currents in the ocean that travel in straight lines, as well as eddies. Furthermore, we consider dividing the ocean current vector into some grids. Since the range of eddies in the Ionian Sea is very huge and the speed of the submersible movement is relatively very small, the ocean current vectors in each grid are linear vectors when drawing the grid.

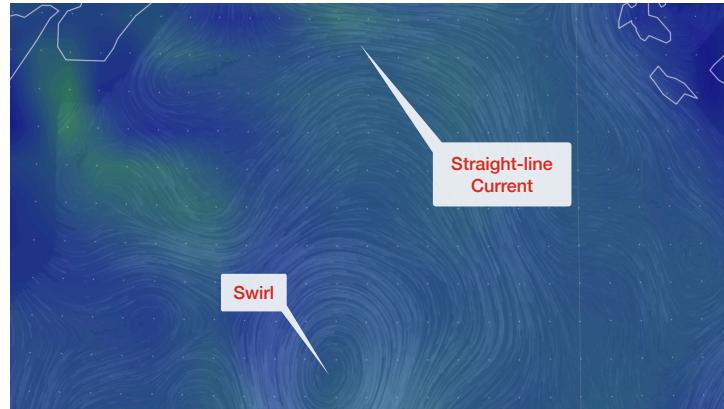


Figure 3: Ocean Currents map of the Ionian Sea

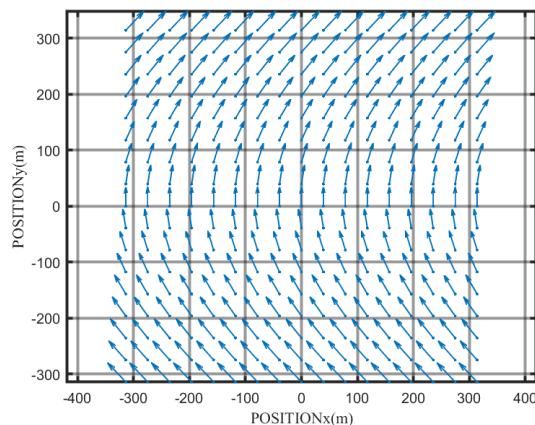


Figure 4: Grid Ocean Current Map

Based on observation data, deep-sea rescue operations last a long time, typically measured in days. This implies that ocean currents may undergo significant changes throughout the duration of a complete rescue mission. Therefore, in our model, we assume that ocean currents are updated every 2 days.

4.3 Model Implementation and Results

In this section, we model the ocean current vectors in the Ionian Sea area. submersible location prediction is performed using the above model, as well as a reduction approach to the uncertainty of the predicted locations.

4.3.1 Submersible Drift Path

We obtain the possible drift paths of the submersible within the limited ocean area based on the previously mentioned current resistance model and the random walk model influenced by the ocean currents. As we can see, there are multiple possible paths, while the route 2 of them pretty much covers most of the paths. To remove some uncertainty, the *Savitzky-Golay Filtering* is used. Below is a diagram of the possible paths after *Savitzky-Golay Filtering*:

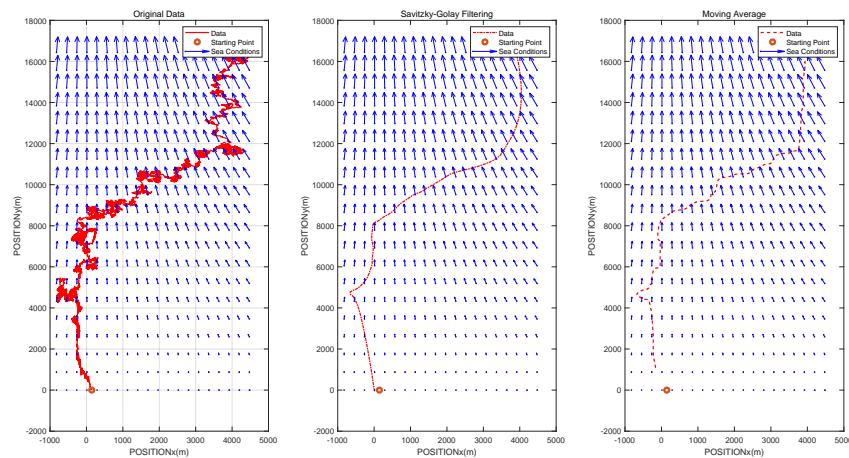


Figure 5: Path Diagram after *Savitzky-Golay Filtering*

We can clearly see that the uncertainty of the path can be reduced to some extent by using *Savitzky-Golay Filtering*.

4.3.2 Submersible Location Prediction

We establish several simulation experiments based on the prediction model via Monte Carlo ideas to further prove the feasibility and significance of the model. First, we predict the coordinates of the location of the submersible after the wreck after different times, and obtain the following probability distribution, as shown in Fig. 6.

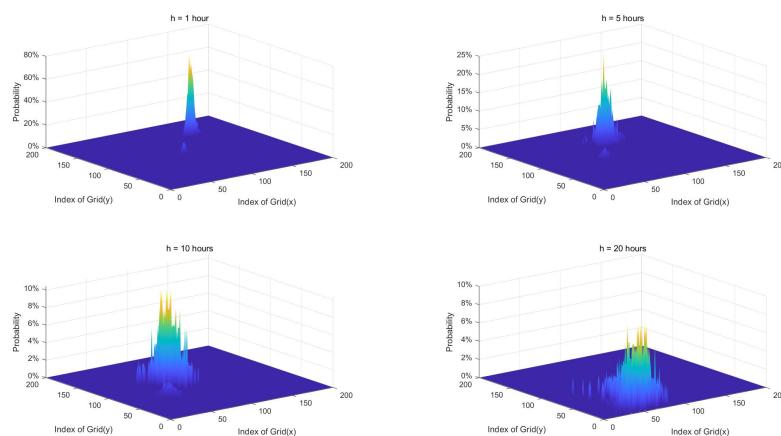


Figure 6: Plot of Probability Distributions after Different Times

We further performed normality test (*Kolmogorov-Smirnov test*) and standard deviation calculations on the above simulated data, and the results of the normality test showed that the original hypothesis of normal distribution was rejected at 1 hour, and normality was significant in all other cases.

The results of standard deviation calculation were as follows:

Table 2: Normality Test

	$x - \text{Coordinate}$	$y - \text{Coordinate}$
1 hour	394.36	764.57
5 hours	1055.225	1335.08
10 hours	2014.69	1614.92
20 hours	2702.95	2035.96

From the above results, it can be seen that the longer the time of the wreck of the submersible, the smaller the initial data information on the prediction of the path gradually, the influence of the random factors of the ocean on the path gradually increases, and the probability distribution tends to be more dispersed, and the difficulty of the search will be greatly increased.

After that, we attempt to simulate two separate scenarios to predict the submersible's location five hours later to demonstrate that the submersible's transmission of initial velocity information reduces uncertainty.

1. The submersible does not report initial velocity information. To simulate this situation, we set the initial velocity to obey a uniform distribution of $[0, v_{max}]$, the direction of the initial velocity to obey a uniform distribution of $[0, 2\pi]$, and the initial location to obey a normal distribution. The probability distribution graph is shown in Fig. 7. This results in a smooth probability distribution graph with very high uncertainty.
2. The submersible reports initial velocity information. The probability distribution graph is shown in Fig. 8. The probability distribution now obtained indicates a very high concentration of probability in one ocean area.

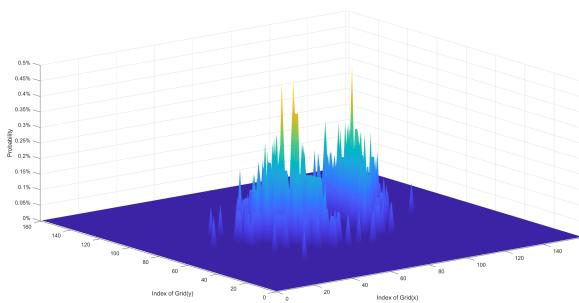


Figure 7: Probability Distribution when Initial Velocity Is not Reported

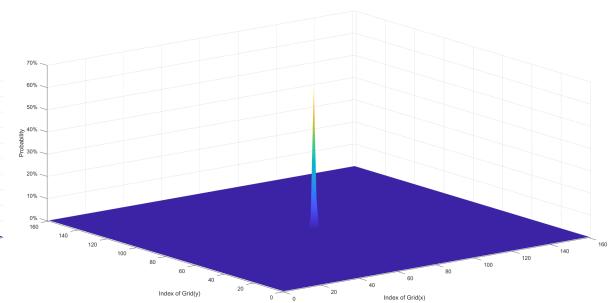


Figure 8: Probability Distribution when Initial Velocity Is Reported

After validation of the above scenarios, it is clear that the submersible's reported initial velocity and the use of *Savitzky-Golay Filtering* to reduce path uncertainty can substantially reduce the uncertainty in predicting the submersible's location.

5 Preparations for the Search

In this section, we integrate large language models (LLMs) with the Analytic Hierarchy Process (AHP) to propose an assessment framework that takes into account factors such as availability, maintenance, readiness and usage for the selection of the optimal underwater probing equipment and rescue equipment. Notice that considering the uniqueness of underwater search and rescue missions, our design allocates reconnaissance and communication tasks to the main vessel, while assigning rescue operations to the rescue ship.

5.1 Evaluation Model Based on AHP and LLMs

In this section, we introduce an approach that applies LLMs to the AHP, illustrating a novel method to enhance the decision-making processes by leveraging the advanced capabilities of LLMs for generating insights and evaluating complex criteria. Using the AHP, once the factors affecting the objective have been identified, a double comparison is made to determine the most favorable factors. However, the classical AHP algorithm is somewhat subjective in determining the weights of each aspect. We innovatively propose an LLM-based scoring scheme to fairly assess the application value and costs of each equipment to ensure that the host vessel and rescue vessel are equipped with the most appropriate detection and rescue equipment, respectively.

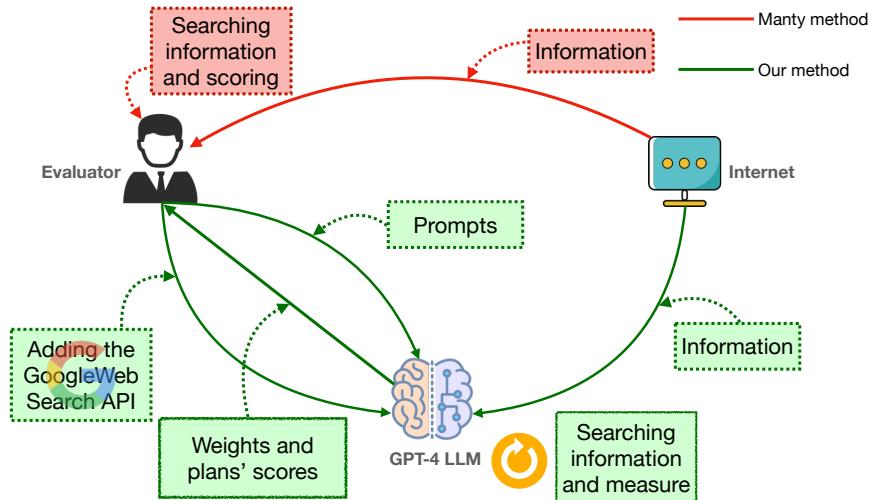


Figure 9: Diagram for Establishing the Evaluation Model

In building the evaluation scheme, we used the GPT-4 (8K) model and added the googleWebSearch API functionality to allow online fact-finding of candidate devices. Previous studies^[5] have validated the effectiveness of GPT-4, the results correlate well with those of human evaluators. To minimize the systematic locational bias^[6], we averaged the results of multiple measurements.

We use prompts engineering techniques, such as a small amount of learning and structured prompts, to guide the GPT-4 in prioritizing and scoring, as detailed in the

"Report on the Use of Artificial Intelligence". The results show that the model effectively utilizes search tools to enhance understanding of candidate devices, thus providing more objective and realistic scores. In addition, we instructed the model to consider all the aspects comprehensively, ensuring the scores reflect the costs and efficiency of the equipment in actual rescue tasks.

5.2 Selection of Probing and Rescue Equipment

In this section, we propose an equipment evaluation scheme that integrates AHP and LLMs, demonstrating the process of constructing a judgment matrix using the probing equipment as an example.

5.2.1 Hierarchy Modeling

Prior to modeling, it is essential to define the scope of the equipment, the dimensions for evaluation, and the ultimate targets. Specifically, the scope for the probing equipment, considering the feasibility on board, includes ROV, acoustic modem, EPIRB, and sonar. Decision criteria will review costs in availability, maintenance, readiness, and usage. Detection capability of each product is also considered. The target of the evaluation model is to select the optimal probing equipment. After these three levels are defined, a hierarchy is constructed by classifying the objectives, factors (decision criteria), and decision targets into the highest, middle, and lowest levels based on their interrelationships. As shown in Fig. 10, it can be seen that the factors at each level are linked to the previous level and may have an impact on the next level.

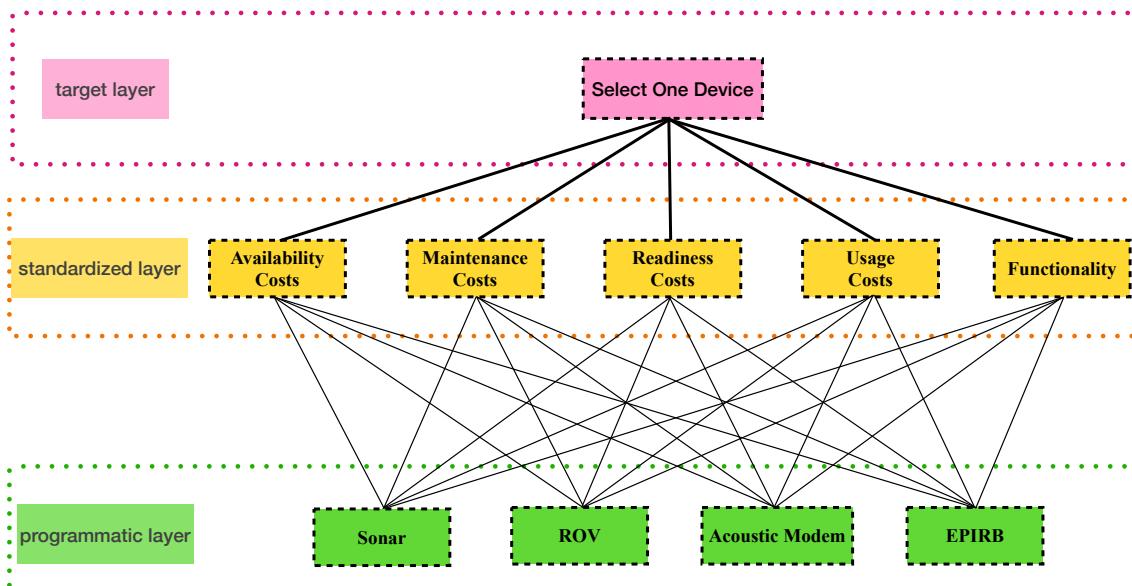


Figure 10: Hierarchy Diagram

5.2.2 Construction of Judgment Matrices

In constructing the judgment matrix, we need to determine the weights of each of the four measures. Here we discard the commonly used Santy method to confirm the importance and instead used the LLMs to calculate the importance of the five evaluation criteria. The following is the generated judgment matrix:

	<i>FUNC</i>	<i>AVAIL</i>	<i>MTCE</i>	<i>READ</i>	<i>USAGE</i>
<i>FUNC</i>	1	1	3	5	1/9
<i>AVAIL</i>	1	1	1	3	1/7
<i>MTCE</i>	1/3	1	1	1	1/7
<i>READ</i>	1/5	1/3	1	1	1/7
<i>USAGE</i>	9	7	7	7	1

Sum each column and divide each cell by its column's total to calculate weights. Then take average for each row:

Table 3: Weights of the Measures

Measures	Weights
Functionality	0.605
Availability	0.174
Maintenance	0.104
Readiness	0.068
Usage	0.053

To test the consistency of the matrix, we calculate the Consistency Ratio (CR), which is defined as the ratio of Consistency Index (CI) to Average Random Consistency Index (RI). The requirements are all met. Thus, the consistency of the matrix is confirmed.

5.3 Model Implementation and Results

In this section, we utilize the proposed evaluation model to rate various types of probing and rescue equipment, and provide the final equipment selection scheme. The following table is obtained by rating some common underwater probing equipment and rescue equipment on the market:

Table 4: Scores of Probing Equipment

Equipment	<i>FUNC</i>	<i>AVAIL</i>	<i>MTCE</i>	<i>READ</i>	<i>USAGE</i>
Multibeam Sonar	9	7	5	7	5
Scanning Sonar	7	5	5	5	7
ROV Hydroid Remus 6000	9	8	7	7	8
Bluefin Robotics BlueROV2	8	4	5	5	4
Acoustic Positioning System	8	4	5	4	5
Acoustic Modem	9	6	5	4	5
Sonobuoy (EPIRB)	9	6	5	6	6

Table 5: Scores of Rescue Equipment

Equipment	<i>FUNC</i>	<i>AVAIL</i>	<i>MTCE</i>	<i>READ</i>	<i>USAGE</i>
AS-31	7	7	5	6	6
DSRV-2	8	6	6	5	7
LR7	7	7	7	6	6
Chang Dao	7	8	6	7	7

Notice: Costs is a negative indicator, thus it is set higher costs result in lower scores.

Based on the total score, we can tell that *ROV Hydroid Remus 6000* (hereafter referred to as ROV) has superior conditions, thus we consider using this ROV for exploration. Employ the same method, for the equipment of the rescue vessel, the *LR7 deep-diving lifeboat* from the UK's *Perry Slingsby Systems* is found to have the highest score, which is selected for the rescue mission.

6 Submersible Search Model

In this section, we establish the search model using a long baseline system as well as a Bayesian search theory. The long baseline communication system utilizes a small range of searches performed by Remotely Operated Vehicles (ROVs). Once the size of the range is obtained, the results of the prediction model are chunked based on the range size. Then, the probability of each chunk is calculated. Finally, the Bayesian search is used to search these chunks.

6.1 Fundamentals of Modeling

In this section, we present the foundational knowledge for the submersible search model as the core of our modeling, including the long baseline communication model and the Bayesian search theory.

6.1.1 Long Baseline Communication Model

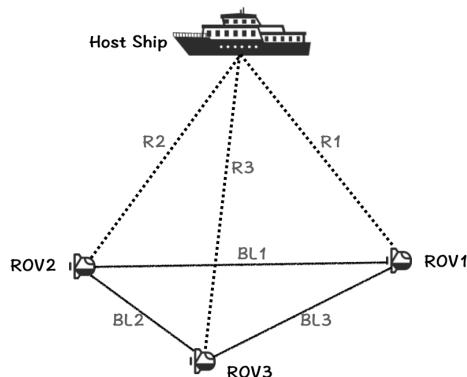


Figure 11: Diagram of Long Baseline Communication System

REMUS 6000's communication capabilities utilize upper and lower long baseline sensors to ensure reliable data transmission and real-time coordination with surface support vessels^[7]. This allows for efficient sharing of critical information and the ability to adjust search strategies as needed.

By leveraging the capabilities of the REMUS 6000, including its depth range, endurance and sensor suite, we propose an optimized search strategy to enhance the efficiency of locating distressed underwater objects and individuals. The search area is defined as a circle with a radius of 50 meters.^[8]

Bayesian Decentralized Data Fusion (DDF) is a method of fusing data collected by multiple ROVs in a system, allowing each ROV maintain a probability density function (PDF) about the system state. By exchanging these PDFs. ROVs can update their estimates of the system state, thereby improving overall estimation accuracy. The core of this approach is to use the Bayes' theorem. As it only shares information relevant to common tasks, this approach can reduce the communication overhead, allowing the system to more efficiently handle large-scale distributed problems.

Throughout the process, the REMUS 6000 communicates with pre-laid DOT using "ping" through its upper and lower long baseline transducers to ensure correct communication between the ROV and control systems. At the same time, its own multibeam sonar also plays a role in helping the ROV avoid obstacles on the seafloor.

6.1.2 Bayesian Search and Rescue

Based on a gridded search region, we first define the state of the target at moment 0 as x_0^t . With the localization model obtained in the first question, we can predict the state of the target at the next moment, which can be represented by the PDF^[9]:

$$\begin{cases} p(x_k^t | z_{1:k}) = K p(x_k^t | z_{1:k-1}) \prod_{i=1}^{N_s} p(z_k^i | x_k^t) \\ K = \frac{1}{\int \left(p(x_k^t | z_{1:k-1}) \prod_{i=1}^{N_s} p(z_k^i | x_k^t) \right) dx_k^t} \end{cases} \quad (14)$$

where x_k^t is a four-dimensional vector including longitude, latitude, velocity in the x-direction, and velocity in the y-direction. Based on the Bayes' Theorem, we can derive the equation^[10]:

$$x_{k+1}^t = f^t(x_k^t, u_k^t, w_k^t) \quad (15)$$

x_k^t as the state vector of the target at moment k , u_k^t as the ROV sampling input including whether the target is detected in the search area, whether there are obstacles, etc. w_k^t as the system noise, including ocean currents, winds, etc. For simplicity, we use Gaussian random noise for simulation.

Then, we define the state of the long baseline communication system acquired at moment k as z_k^s , which consists of the states of the multiple ROVs. The iteration of z_k^s follows the equation^[11]:

$$z_k^s = h^s(x_k^s, v_k^s) \quad (16)$$

where x_k^s represents the state of the system at moment k and v_k^s represents the observation noise. The advantage of this localization system is that it can synthesize multiple sensor sampling scenarios to improve the accuracy of the prediction.

The last state transmitted before the submersible is lost is first used as the prior probability, and the posterior probability x_1^t is obtained by the prediction model.

Once it receive the data, it turns into *Stage 2*. At this point, the long baseline system under the control of the MPC starts the search work and does the next iteration according to the searched grid to get x_2^t . Repeat this process until there is a ROV locates the target submersible.

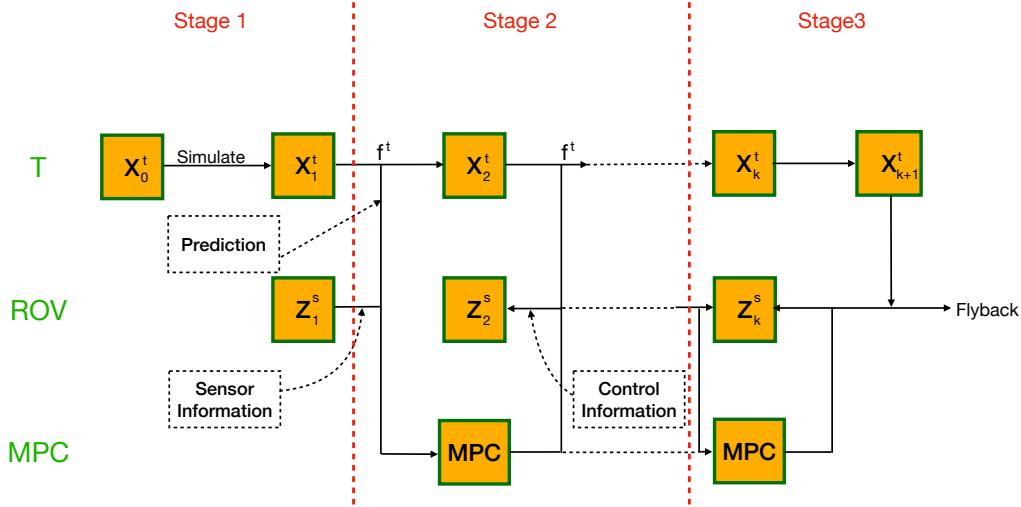


Figure 12: The three stages of search

After the dual-frequency swept sonar on the ROV searches for the submersible, it turns into *Stage 3*, the MPC system guides the ROV to keep moving closer to the target, and during this iterative process, the predicted probability density gets larger. Until the sampled information reaches our pre-set metrics (PDF > 0.9, High Resolution Camera on the ROV identifies the target submersible), we consider the target submersible found, and then we can proceed with the rescue.

We carry out optimal control through MPC to ensure that the long baseline system always searches along the shortest path, and at the same time, the cooperative work of multiple ROVs greatly improves the accuracy of the prediction, and in this way, we achieve the required goal of minimizing the search time.

6.2 Search Model Establishment

1. Considering that the ROV can travel at speeds up to $2.6\text{km}/\text{h}$, when calculating the rescue cycle, we account for the delay time it takes for the search system to move to an adjacent grid. This delay time is only related to the unit rescue time and the number of search areas.
2. Considering the complexity of the real situation and the flexibility of decision-making, we define the relationship between the success probability q and the current zone rescue time t_s :

$$q = -(t_s - 1)^2 + 1, \quad 0 < t_s < 1 \quad (17)$$

From the above equation, it can be seen that when t_s increases, the growth rate of search and success probability q shows a trend of first fast and then slow, which is in line with the reality.

3. Considering the fact that the initial information of a submersible with an accident reduces the prediction uncertainty faster over time, and the information entropy increases significantly, we include the consideration of the delay time in rescue.
4. Considering that ROVs are often equipped with embedded automatic control systems, which require certain model size and algorithmic efficiency, we propose an adaptive search strategy inspired by the behavior of insects searching for locations with high odor concentrations. In this strategy, the searching individual plans each path by detecting along that path and updating the confidence graph in real-time, and the strategy can be expressed as:

$$k^t = \begin{cases} \text{peak}(k+1), & \lambda(t) = \lambda(t-1) \\ \text{newpeak}(1), & \lambda(t) \neq \lambda(t-1) \end{cases} \quad (18)$$

where $\lambda(t)$ denotes the probability peak point of the search region at time t . The algorithm is computationally small and efficient for microprocessors and embedded devices since it focuses only on the grid cells with maximum probability in each planning process.

5. We consider a prediction model based on the first question that updates the prior probability distribution of the lattice according to a certain period.

In summary, we choose to optimize the *Mean Time to Detection* (MTTD) using simulated annealing algorithm. In the iterative process, based on the idea of *Monte Carlo* method, we establish several experiments to obtain the time expectation, and make the time expectation gradually converge to the global optimum.

6.3 Model Implementation and Results

First, we update the lattice probability distribution once at each time point based on the Bayesian formula, and based on a given lattice probability distribution, we obtain an update of the probability distribution over the search time as shown below:

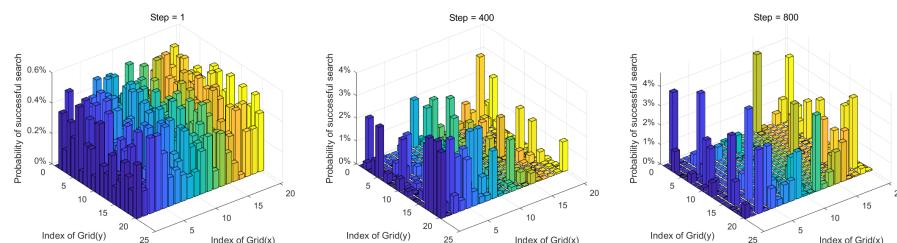


Figure 13: The Probability Distribution over the Search Time

Then, for the lattice, we combine the prediction model of the first question with a real-time prediction of the prior probability distribution, and assume that the probability matrix update is transmitted to the ROV every 2 hours. In a rescue plan, we obtain a cumulative probability function as shown in the following figure:

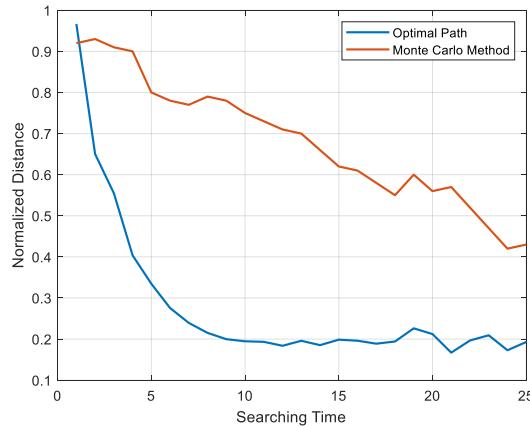


Figure 14: Normalized Distance

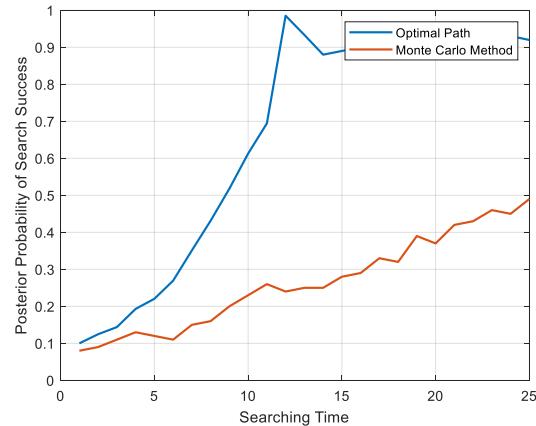


Figure 15: Posterior Probability

It can be seen that the optimal path obtained by planning is of better quality compared to the Monte Carlo method based on simple repeated experiments. Meanwhile, based on the data of a posterior probability in the above figure, we can point out what is the probability of successful search at a fixed point in time, and further estimate the probability of successful search at any moment by interpolation.

Finally, we use the simulated annealing algorithm for planning solution. The optimal results are obtained as follows:

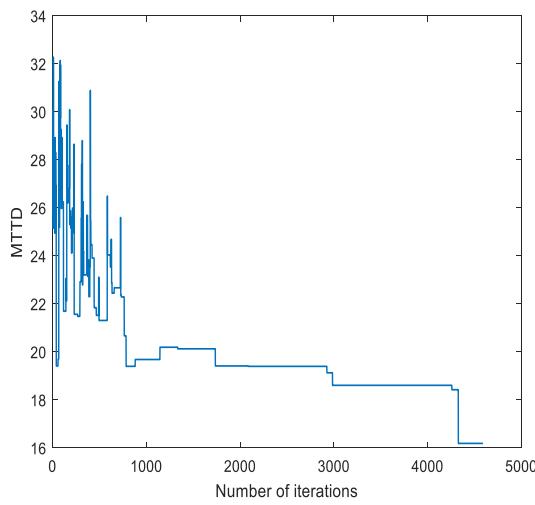


Figure 16: Simulating the Iterative Process of Annealing Algorithm

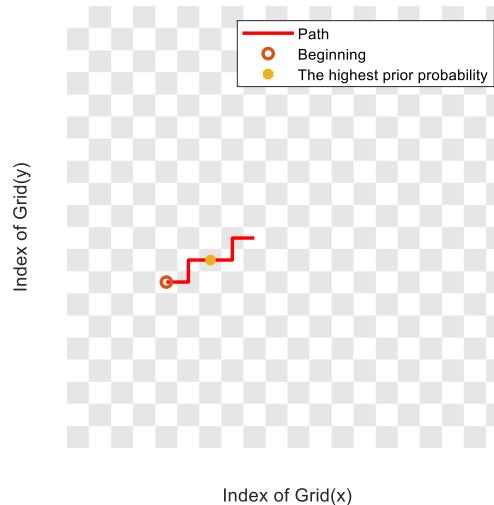


Figure 17: Optimal Path

It is basically certain that the algorithm has converged to a globally optimal solution.

7 Model Extrapolation

The model we built is highly scalable and can be extended to other tourist destinations by changing only some of its parameters. We need to modify the ocean current vector of the prediction model due to the different distribution of ocean currents in different seas.

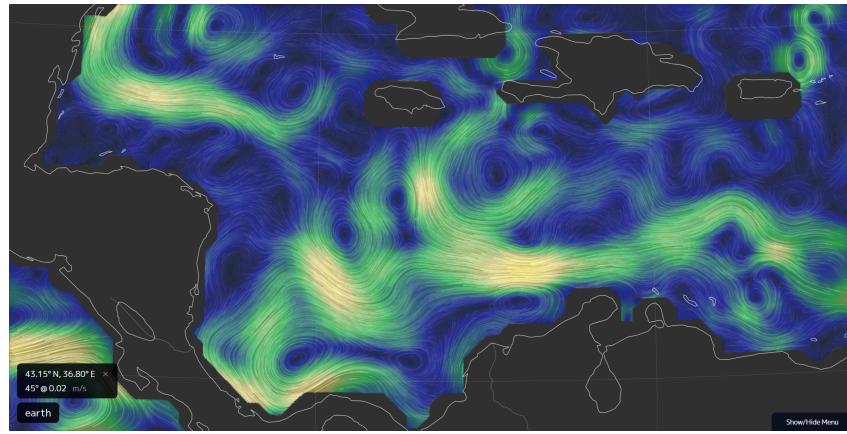


Figure 18: Currents in the Caribbean Sea.

For instance, for the Caribbean Sea, according to the literature, it is known that the ocean topography and current distribution in the Caribbean Sea is more complicated than that in the Ionian Sea. Since we use normally distributed random variables to represent the drastic changes in seawater parameters and their drastic effects on the location of the submersible, we consider increasing the variance of the random variables and the random coefficients of the oceanic factors in order to quantify the environmental differences in the Caribbean Sea and thus extrapolate our model.

Next, compared to the initial values of the ocean parameters in the Ionian Sea, we set the parameters to two times their values for predictive analysis and search strategy planning to obtain the grid probability distribution and optimal search strategy for 5 hours:

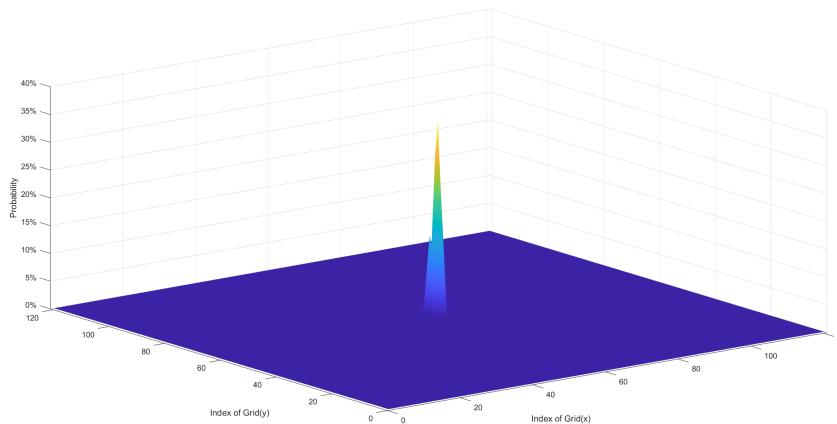


Figure 19: the Probability Distribution over the Search Time

It can be seen that the grid probability distribution is more concentrated, indicating that the model is also effective for the more complex marine environment of the Caribbean Sea.

For multiple submersible moving in the vicinity of the same location. In the event that one submersible is wrecked, the remaining submersible can be used as ROVs to form a long baseline location system to quickly search the perimeter and determine the location of the wrecked submersible, which will dramatically reduce the time it takes for the main ship to get to the area of the incident.

8 Sensitivity Analysis

In our previous model, there are some parameters and that can be varied depending on the situation.

σ_k : The sea state coefficient that quantifies magnitude of changes in seawater parameters due to climate and other factors.

γ : The marine terrain index that quantifies the complexity of the marine topography.

$dist_{cur}$: The type of ocean current distribution, contains information such as the shape of the overall distribution of ocean currents, the average speed, etc., and is a fixed-type variable.

Based on this, we adjust these parameters to test the sensitivity and robustness of our model.

In order to facilitate a cross-sectional comparison of the effectiveness of the system, we introduce the system gain G as a quantitative assessment metric. G is defined as the percentage of the total area of regions that are considered to exceed a certain confidence threshold in the total area of the grid map, for a given moment in time, when assessing the probability of the distribution of the range of search results through the system. As a rule of thumb, the confidence threshold is set to 0.85.

Next, we will use the parameters of the Ionian Sea and the system gain as a reference, i.e., we will set its G to 1, and then calculate the relative gain G_R for the other cases.

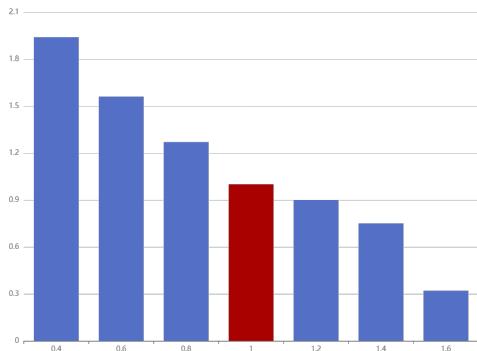


Figure 20: System with G different σ_k

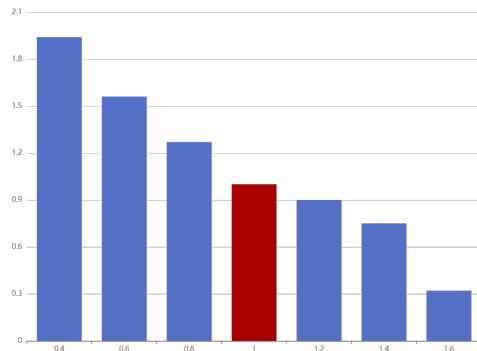


Figure 21: System G with different γ

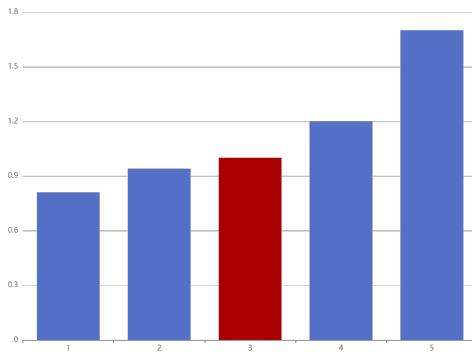


Figure 22: System G with different $dist_{cur}$

The ocean currents are selected and varied with several classical kinds of currents, which can be roughly categorized into eddy, direct current and superposition states. Based on the above analysis, it can be seen that the system gain is very high in the case of a small degree of influence of environmental factors, and in the case of a large environmental influence, the model can still ensure good accuracy and effectiveness, which shows that the model is robust and suitable for application in various regions.

9 Strengths and Weaknesses

1. Strengths

- Our model can predict the location of the submersible while confirming the search scenario. Furthermore, it can provide detailed selections of the equipment.
- Our model combines a number of factors to obtain a generalized scenario, and allows for a more accurate prediction of submersible locations based on current direction and ocean parameters.
- We utilize a variety of models and algorithms, and optimize them several times to get the best results. Instead of overemphasizing the process of these algorithms, we vividly describe the modeling ideas, and each principle is accompanied by an explanation to make it easier to make sense of the problem solving.
- Our model is highly scalable and can be used in other ocean areas by modifying some parameters.
- We innovatively propose an evaluation model using AI plus AHP, and obtain objective evaluation scores.

2. Weaknesses

- Some unpredictable and unmeasurable impacts are ignored in the elements we discuss and may bias the predictive modeling of our model, thus affecting our probing scenarios.
- There may be other factors that affect our model, but we have paid less attention to them, which may cause some bias.

MEMORANDUM

To: Government of the Hellenic Republic

From: Maritime Cruises Mini-submersibles (MCMS)

Subject: Report for Approval of Deep-Sea Adventure Tourism Project

Date: February 5, 2024

Executive Summary

Based on our comprehensive safety assessment and the development of a dependable search and rescue strategy, we recommend the approval of the Maritime Cruise Mini submersible (MCMS) for deep-sea adventure tourism in the Ionian Sea.

Through the measures mentioned below, MCMS can provide visitors with a safe and exciting deep-sea experience while maintaining the highest safety standards. This will enhance the company's reputation and make a positive contribution to the local economy and the Greek tourism industry.

Background

Our assessment is conducted against the backdrop of the unique challenges posed by deep-sea exploration, including the need for reliable communications and the unpredictability of the ocean environment. We collect data from a variety of sources, including historical records of submersible project, oceanographic studies, and technical specifications of the equipment under consideration. We use a combination of qualitative and quantitative methods to analyze the data, focusing on risk assessment and probabilistic modeling.

Bayesian search model is the cornerstone of our strategy. The model has been tested against simulated scenarios to ensure its effectiveness in predicting the submersible location and guiding search efforts. The models for which we have performed simulations have strong reliability, ensure that the submersible can be found in the shortest possible time. Next we show our specific security model.

Security Model

1. Establish a model to predict the location of the submersible. In the process of building the model, we consider the influence of ocean currents, seawater density, and ocean topography on the movement of the submersible. We add the perturbations caused by the above factors to the model based on Random Walk model. We simulate the location prediction and path prediction of the submersible by extracting the Ionian ocean currents data and other factors.

2. Establish a search model. With a predictive model of the submersible position, we build a search model based on the Bayesian search algorithm. In the search model, we combine the long baseline communication system as well as MPC to provide a solution that minimizes the search time. In our simulation, the exact location of the submersible can be detected soonly.

3. We also consider the selection of search and rescue equipment. We innovatively provide an evaluation method that combines LLM and AHP to avoid subjectivity. We finally select the search equipment and rescue equipment with the highest scores. We select *ROV Hydroid Remus 6000* as the search equipment and *LR7 deep-diving lifeboat* as the rescue equipment.

Search Time

The probability of searching for a wrecked submersible in the Ionian Sea is about 90% for an average of 12 hours of searching; for an average of 10 hours of searching, the distance to the wrecked submersible is less than 0.2 min/km.

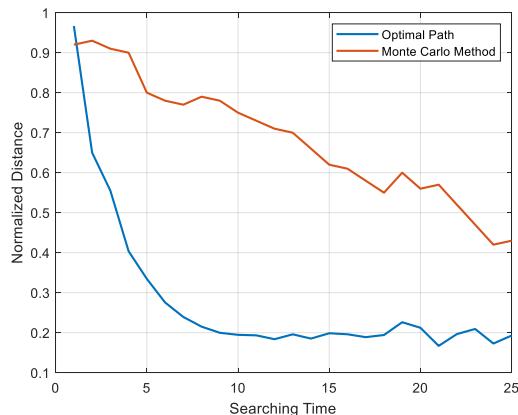


Figure 1: Normalized Distance

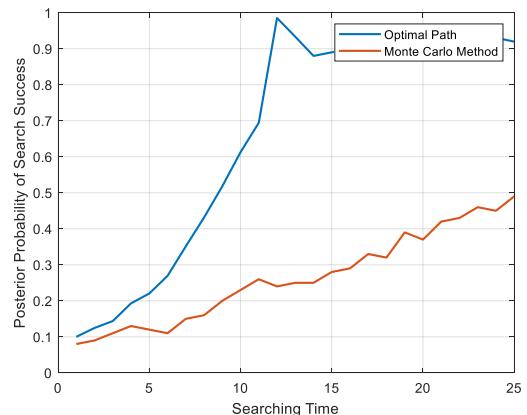


Figure 2: Posterior Probability

We have very advanced models that significantly improve the safety of the submarine. And have the ability to deal effectively with emergencies as they arise. Moreover, our model is highly scalable and flexible, and can be easily adapted to other sea areas. If we can carry out marine exploration activities in the Ionian Sea, we believe that soon the world will gradually adopt our model. We look forward to working with governments to ensure the safety of submarines and to contribute to national ocean exploration.

Sincerely,

MCMS
February 5, 2024

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Report on the Use of AI

1. OpenAI ChatGPT (Feb3,2024 version, Call API, GPT-4(8K))

Query1 : Task Description: " You are acting as an evaluator and will use the Analytic Hierarchy Process (AHP) to rate a series of candidate rescue equipment. You are tasked with evaluating and selecting the most suitable rescue equipment for a maritime search and recovery operation. The operation involves deploying submersibles from a mothership, which may become disabled or lose communication in deep-sea environments. The goal is to ensure that the mothership is equipped with the necessary tools to locate and recover these submersibles efficiently and safely. Please compare each pair of equipment based on the following evaluation criteria and provide a corresponding score.

Evaluation Criteria: 1. Availability Costs: This refers to the expenses related to acquiring the equipment, shipping it, and ensuring that it is accessible and ready for use when needed. 2. Maintenance Costs: These are the ongoing costs for routine maintenance, periodic inspections, and any necessary repairs or replacements of parts to keep the equipment functioning properly. 3. Readiness Costs: This involves the costs associated with keeping the equipment in a state of readiness, which may include inventory costs for spare parts and the training and wages of maintenance staff. 4. Usage Costs: These are the costs incurred during the actual operation of the equipment, such as energy consumption, consumables, and any other expenses that arise from using the equipment. 5. Functionality: The equipment's ability to perform its intended task, its efficiency, and the range of operations it can handle. This is a key factor in determining whether the equipment meets the specific requirements of a project or tasks.

Scoring Criteria: - 1: Equal importance. - 3: Slightly more important. - 5: Strongly more important. - 7: Very strongly more important. - 9: Extremely more important. - Intermediate values (2, 4, 6, 8): Indicate varying degrees of importance.

Scoring Process: 1. Construct a Judgment Matrix: For each pair of evaluation criteria (e.g., Maintenance vs. Availability), construct a judgment matrix. Rate each pair based on their importance in the context of a rescue mission. 2. Consistency Check: Ensure that your scoring matrix is logically consistent. If necessary, adjust the scores to meet consistency requirements. 3. Calculate Weights: Calculate the weight of each evaluation criterion based on the judgment matrix. The weight is the proportion of each criterion in the total score. 4. Evaluate Equipment: For each candidate equipment, rate it according to the evaluation criteria. If you do not understand a piece of equipment, you can use a web search. Ensure that each piece of equipment's score reflects its performance on each criterion. 5. Aggregated Score: Multiply each piece of equipment's scores on each criterion by the corresponding weight, then sum them up to get the total score for each piece of equipment. Your answer should contain the scores, for example, using the example given above, if you wish to give "A" an availability costs score of 5, a maintenance costs score of 3, a readiness costs score of 4, a usage costs score of 5 and a functionality score of 5, and you wish to give "B" an availability costs score of 7, a maintenance costs score of 3, a readiness costs score of 3, a usage costs score of 8 and a functionality score of 9. then you should return the following output: "A": "Availability Costs": 5, "Maintenance Costs": 3, "Readiness Costs": 4, "Usage Costs": 5, "Functionality": 5, "B": "Availability Costs": 7, "Maintenance Costs": 3, "Readiness Costs": 3, "Usage Costs": 8, "Functionality": 9,

Notes: - When scoring, consider the long-term benefits and potential risks of the equipment.
- Ensure that your scores reflect the performance and efficiency of the equipment in actual rescue missions.
- If multiple pieces of equipment perform similarly on some criteria, consider other factors such as the equipment's reliability record, supplier support, and the equipment's upgradability.

Based on these guidelines, please rate the following candidate equipment, and provide your recommended selection. Do you understand?"

Output1 : "Yes, I understand my task. I am to evaluate a set of candidate rescue equipment using the Analytic Hierarchy Process (AHP). The evaluation will be based on four criteria namely: Availability, Maintenance, Readiness, and Usage. I will assign scores to each equipment according to these criteria and make a final recommendation based on my evaluation."

Query2: "now I give you candidate rescue equipment: 'multibeam sonar', 'scanning sonar', 'Bluefin Robotics BlueROV2', 'ROV Hydroid Remus 6000', 'Long Baseline Acoustic Positioning System', 'underwater communication system (Acoustic Modem)', 'sonobuoy (EPIRB)'"

Output2 : " Here are my evaluation scores for each piece of equipment based on the criteria we established: "json "Multibeam sonar": "Availability Costs": 7, "Maintenance Costs": 5, "Readiness Costs": 7, "Usage Costs": 5, "Functionality": 9, "Scanning Sonar": "Availability Costs": 5, "Maintenance Costs": 5, "Readiness Costs": 5, "Usage Costs": 7, "Functionality": 7, "Bluefin Robotics BlueROV2": "Availability Costs": 8, "Maintenance Costs": 7, "Readiness Costs": 7, "Usage Costs": 8, "Functionality": 9, "ROV Hydroid Remus 6000": "Availability Costs": 4, "Maintenance Costs": 5, "Readiness Costs": 5, "Usage Costs": 4, "Functionality": 8, "Long Baseline Acoustic Positioning System": "Availability Costs": 4, "Maintenance Costs": 5, "Readiness Costs": 4, "Usage Costs": 5, "Functionality": 8, "Underwater communication system (Acoustic Modem)": "Availability Costs": 6, "Maintenance Costs": 5, "Readiness Costs": 6, "Usage Costs": 6, "Functionality": 9, "Sonobuoy (EPIRB)": "Availability Costs": 8, "Maintenance Costs": 6, "Readiness Costs": 8, "Usage Costs": 7, "Functionality": 8 " Based on the scores, my recommendation would be the 'ROV Hydroid Remus 6000' as it has consistently high scores across all the criteria, and especially excelled in "Availability" and "Readiness", which are crucial in rescue operations. However, for ease of operation and adaptability, the 'Bluefin Robotics BlueROV2' stands out as well. It's strongly suggested to consider multiple equipments for different scenarios and backup options. Please note that these scores and recommendation are made based on certain assumptions and should be further adjusted with your team's specific needs and situational awareness. "

Query3 : "now give me a detailed evaluation using the Analytic Hierarchy Process (AHP)" ,

Output3 : " Sure, I would be glad to provide a more detailed evaluation using the Analytic Hierarchy Process. Here's how I would score the selected pieces of equipment: 1. Construct a Judgment Matrix: Recalling the scoring criteria, the weights are as follows: "Availability Costs" is scored from 4 to 8, so let's give it a weight of 1/7. "Maintenance Costs" is scored 5 for all, so let's give it a weight of 1/7. "Readiness Costs" is scored from 4 to 8, so let's give it a weight of 1/7. "Usage Costs" is scored from 4 to 8, so let's give it a weight of 1/7. "Functionality" is scored from 7 to 9, being the most important. So, let's give it a weight of 3/7. " 2. Consistency Check: This is a reciprocal matrix and it is logically consistent: rows are consistent, and every entry a_{ij} is the reciprocal of a_{ji} . 3. Calculate Weights: now calculate the final score for each piece of equipment using the weights. "Multibeam sonar": "Weighted Score": $1/7*7 + 1/7*5 + 1/7*7 + 1/7*5 + 3/7*9 = 7.86$, "Scanning Sonar": "Weighted Score": $1/7*5 + 1/7*5 + 1/7*5 + 1/7*7 + 3/7*7 = 6.71$, "Bluefin Robotics BlueROV2": "Weighted Score" : $1/7*4 + 1/7*5 + 1/7*5 + 1/7*4 + 3/7*8 = 6.14$

, "ROV Hydroid Remus 6000": "Weighted Score" : $1/7*8 + 1/7*7 + 1/7*7 + 1/7*8 + 3/7*9 = 8.29$
 "Long Baseline Acoustic Positioning System": "Weighted Score" : $1/7*4 + 1/7*5 + 1/7*4 + 1/7*5 + 3/7*8 = 6.14$, "Underwater communication system (Acoustic Modem)": "Weighted Score" : $1/7*6 + 1/7*5 + 1/7*6 + 1/7*6 + 3/7*9 = 7.57$, "Sonobuoy (EPIRB)": "Weighted Score" : $1/7*8 + 1/7*6 + 1/7*8 + 1/7*7 + 3/7*8 = 7.71$ "

Query4 : " Analyse the following equipments: US Navy's DSRVs(DSRV-1 and DSRV-2), UK's LR series(LR5 and LR7), Russian AS-31, Chinese "Ocean Island" and "Changdao" "

Output4 : " My matrix and scores based on the AHP guidelines provided would look something like this: Judgment Matrix: — Criteria — Availability Costs — Maintenance Costs — Readiness Costs — Usage Costs — Functionality —

— Availability Costs — 1 — 3 — 4 — 2 — 1/2
 — — Maintenance Costs — 1/3 — 1 — 1/2 — 1/4 — 1/6 — — Readiness Costs — 1/4 — 2 —
 1 — 1/3 — 1/5 — — Usage Costs — 1/2 — 4 — 3 — 1 — 1/3 — — Functionality — 2 — 6 —
 5 — 3 — 1 — Following this, we check for consistency and adjust as needed. The weights for each criterion are calculated from this judgment matrix. Given a consistent and weighted matrix, scoring for the equipment might look something like this: {"json": "DSRV-1": "Availability Costs": 6, "Maintenance Costs": 5, "Readiness Costs": 5, "Usage Costs": 5, "Functionality": 7, "DSRV-2": "Availability Costs": 7, "Maintenance Costs": 6, "Readiness Costs": 4, "Usage Costs": 6, "Functionality": 8, "LR5": "Availability Costs": 5, "Maintenance Costs": 3, "Readiness Costs": 3, "Usage Costs": 5, "Functionality": 6, "LR7": "Availability Costs": 6, "Maintenance Costs": 4, "Readiness Costs": 2, "Usage Costs": 4, "Functionality": 7, "AS-31 (Losharik)": "Availability Costs": 2, "Maintenance Costs": 5, "Readiness Costs": 6, "Usage Costs": 3, "Functionality": 9, "Hai Jiao": "Availability Costs": 6, "Maintenance Costs": 7, "Readiness Costs": 7, "Usage Costs": 5, "Functionality": 8, "Changdao": "Availability Costs": 8, "Maintenance Costs": 6, "Readiness Costs": 5, "Usage Costs": 7, "Functionality": 9} To determine the final score: 1. Multiply each rating by appropriate weights derived from the judgment matrix. 2. Sum up the weighted scores for each equipment. The equipment with the highest final aggregated score would be the most suitable for the maritime search and recovery operation. It appears, based on the raw scoring provided, that the "Changdao" would be the final choice due to its high score"

Query5 : " go ahead "

Output5 : " Apologies for the oversight. Let's calculate the weights from the judgment matrix provided earlier and compute the final scores for each piece of equipment. Based on the judgment matrix, after normalizing and averaging, let's assume we derive the following weights for criteria (please note that these weights should technically be calculated using an Eigenvalues process, but here for simplicity, we're approximating): - Availability Costs: 0.15 - Maintenance Costs: 0.10 - Readiness Costs: 0.20 - Usage Costs: 0.25 - Functionality: 0.30 Now, using these weights, we will calculate the final scores for each equipment. Below is the calculation based on the sample scores provided: {"json": "DSRV-1": "Availability Costs": 6 * 0.15, "Maintenance Costs": 5 * 0.10, "Readiness Costs": 5 * 0.20, "Usage Costs": 5 * 0.25, "Functionality": 7 * 0.30, "DSRV-2": "Availability Costs": 7 * 0.15, "Maintenance Costs": 6 * 0.10, "Readiness Costs": 4 * 0.20, "Usage Costs": 6 * 0.25, "Functionality": 8 * 0.30, "LR5": "Availability Costs": 5 * 0.15, "Maintenance Costs": 3 * 0.10, "Readiness Costs": 3 * 0.20, "Usage Costs": 5 * 0.25, "Functionality": 6 * 0.30, "LR7": "Availability Costs": 6 * 0.15, "Maintenance Costs": 4 * 0.10, "Readiness Costs": 2 * 0.20, "Usage Costs": 4 * 0.25, "Functionality": 7 * 0.30, "AS-31 (Losharik)": "Availability Costs": 2 * 0.15, "Maintenance Costs": 5 * 0.10, "Readiness Costs": 6 * 0.20, "Usage Costs": 3 * 0.25, "Functionality": 9 * 0.30, "Hai Jiao": "Availability Costs": 6 * 0.15, "Maintenance Costs": 7 * 0.10, "Readiness Costs": 7 * 0.20, "Usage Costs": 5 * 0.25, "Functionality": 8 * 0.30, "Changdao": "Availability Costs": 8 * 0.15, "Maintenance Costs": 6 * 0.10, "Readiness Costs": 5 * 0.20, "Usage Costs": 7 * 0.25, "Functionality": 9 * 0.30}

0.10, "Readiness Costs": 7 * 0.20, "Usage Costs": 5 * 0.25, "Functionality": 8 * 0.30 , "Changdao": "Availability Costs": 8 * 0.15, "Maintenance Costs": 6 * 0.10, "Readiness Costs": 5 * 0.20, "Usage Costs": 7 * 0.25, "Functionality": 9 * 0.30 " Next, to get the final score for each equipment, we would add these weighted values: For example, the "Changdao" would have: - Availability Costs: 8 * 0.15 = 1.2 - Maintenance Costs: 6 * 0.10 = 0.6 - Readiness Costs: 5 * 0.20 = 1.0 - Usa "

2. Perplexity (Feb 3, 2024 version)

Query1 : "Imagine a scenario where you have lowered some submersibles from the mother ship. These submersibles may suddenly lose power and communication. At this time, you need to send a rescue ship to search and rescue. Please try your best to collect information online and recommend search and rescue equipment that needs to be carried on the mother ship, such as sonar systems, unmanned submersibles (ROVs), underwater communication equipment, etc. The selection of these equipment should be based on considerations such as cost associated with availability, maintenance, readiness and usage of this equipment."

Output1 : " When considering factors such as cost, maintenance, readiness and usage, the search and rescue equipment carried on the mother ship should be efficient, reliable and economical. Here are some recommended search and rescue equipment: 1. **SONAR SYSTEM**: The sonar system is a key tool for underwater search and rescue. It can detect the position of the submersible. The selection should consider its detection range, resolution and depth, as well as the durability and maintenance costs of the system. Portable sonar equipment may be more suitable for rapid deployment but may be limited in depth and accuracy. Fixed-installation advanced sonar systems may cost more but provide more accurate detection capabilities. 2. **Unmanned Vehicles (ROVs)**: ROVs can conduct detailed searches and possible intervention in the vicinity of submersibles that have lost power and communications. When selecting ROVs, you should consider their operating depth, maneuverability, the sensors they carry (e.g., cameras, sonar), and the complexity of maintenance and operation. ROVs may have higher maintenance costs, but their role in search and rescue missions is irreplaceable. 3. **Underwater communication equipment**: In order to maintain communication with submersibles or ROVs, you may need to carry underwater communication equipment, such as acoustic modems. These devices should have good signal transmission capabilities, taking into account their durability and maintenance requirements. 4. **Rescue Boat and Towing Equipment**: After locating the submersible, a rescue boat and towing equipment may be required to bring it back to the mother ship. These devices should have sufficient power and stability while taking into account ease of operation and cost-effectiveness. 5. **Diving Equipment**: If divers need to directly participate in search and rescue, they should bring appropriate diving equipment, including diving suits, respirators, diving helmets, etc. The maintenance and readiness of this equipment is critical to ensure it can be quickly put into use in the event of an emergency. 6. **Unmanned Aerial Vehicles (UAVs)**: UAVs can be used for searches on the water, especially in vast sea areas. They can cover large areas quickly and at relatively low cost. However, the flight height and field of view angle of the UAV may limit its application in complex sea conditions. When selecting these equipment, a cost-benefit analysis should be conducted to ensure that the equipment can be quickly put into use at critical times, while taking into account long-term maintenance and operating costs. In addition, equipment training and operator skills are also important factors, ensuring that team members are familiar with the use and maintenance of the equipment. Finally, device compatibility and interoperability should also be taken into consideration to enable efficient operation when multiple devices work together. "

Query2 : "I want to use GPT-4 as an reviewer. Please help me write a detailed prompt to tell

him to rate these candidate devices."

Output2 : " Certainly! Here's a detailed prompt in English for GPT-4 to rate the selection of rescue equipment using the Analytic Hierarchy Process (AHP):

****Task Description:**** You are acting as an evaluator and will use the Analytic Hierarchy Process (AHP) to rate a series of candidate rescue equipment. Please compare each pair of equipment based on the following evaluation criteria and provide a corresponding score.

****Evaluation Criteria:****

1. Cost (C): Including procurement cost, operational cost, maintenance cost, and labor cost.
2. Availability (A): The probability of the equipment functioning normally when needed, and the maintenance cycle.
3. Maintenance (M): Maintenance frequency, difficulty of maintenance, and maintenance cost.
4. Readiness (R): Startup time, response time.
5. Usage (U): Ease of operation, adaptability, and compatibility.

****Scoring Criteria:****

- 1: Equal importance. - 3: Slightly more important. - 5: Strongly more important. - 7: Very strongly more important. - 9: Extremely more important. - Intermediate values (2, 4, 6, 8): Indicate varying degrees of importance.

****Scoring Process:****

1. ****Construct a Judgment Matrix**:** For each pair of evaluation criteria (e.g., Cost vs. Availability), construct a judgment matrix. Rate each pair based on their importance in the context of a rescue mission.
2. ****Consistency Check**:** Ensure that your scoring matrix is logically consistent. If necessary, adjust the scores to meet consistency requirements.
3. ****Calculate Weights**:** Calculate the weight of each evaluation criterion based on the judgment matrix. The weight is the proportion of each criterion in the total score.
4. ****Evaluate Equipment**:** For each candidate equipment, rate it according to the evaluation criteria. Ensure that each piece of equipment's score reflects its performance on each criterion.
5. ****Aggregated Score**:** Multiply each piece of equipment's scores on each criterion by the corresponding weight, then sum them up to get the total score for each piece of equipment.

****Notes:****

- When scoring, consider the long-term benefits and potential risks of the equipment.
- Ensure that your scores reflect the performance and efficiency of the equipment in actual rescue missions.
- If multiple pieces of equipment perform similarly on some criteria, consider other factors such as the equipment's reliability record, supplier support, and the equipment's upgradability.

Based on these guidelines, please rate the following candidate equipment and provide your recommended selection.

Please note that this prompt assumes GPT-4's ability to understand and execute the AHP scoring process. In actual application, you may need to adjust the prompt according to GPT-4's actual capabilities."

Query3 : "Recommend several commonly used ROVs suitable for underwater search and rescue"

Output3 : " Based on the search results and general knowledge, here are several commonly