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Assessing the Effectiveness of Marine Robotics Technologies for Marine Oil Spill and Microplastic Mitigation: A Comparative Study

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ABSTRACT

This study assessed the effectiveness of marine robotics technology in combating marine oil spills and microplastic pollution. Rising environmental concerns in marine environments require novel solutions, resulting in the use of modern technologies. This study seeks to determine the best maritime robotics technology based on major characteristics, such as adaptability, efficiency, safety, and cost. To achieve this, a hybrid of multi-criteria decision-making methods (MCDM), including the Genetic Algorithm (GA), Analytic Hierarchy Process (AHP), and Grey Relational Analysis–Technique for Order Preference by Similarity to Ideal Solution (GRA-TOPSIS), was proposed and implemented. The main findings of the study revealed that Unmanned Underwater Gliders (UUGs) performed best, followed by Wave Gliders and Unmanned Surface Vehicles (USVs). A sensitivity analysis validated the robustness of these rankings. These findings highlight the importance of prioritizing the development and deployment of UUGs and Wave Gliders to manage maritime oil spills and microplastic contamination. The research did not focus on a specific geographic region but provided insights applicable to global marine pollution management and the deployment of a novel hybrid of multi-criteria decision-making methods. Moreover, this research highlights the importance of optimizing and enhancing the performance of UUGs, Wave Gliders, and Autonomous Underwater Vehicles (AUVs) to effectively mitigate environmental risks in marine ecosystems. The study also introduces a novel hybrid MCDM method called GAGT (GA-AHP-GRA-TOPSIS), which is a combination of various MCDM techniques used in the study, and provides useful insights for policymakers, environmental agencies, and researchers working on marine pollution mitigation efforts, emphasizing the critical significance of cutting-edge marine robotics technologies in protecting marine ecosystems. The hybrid technique was able to capitalize on the strengths of each method, improving the overall decision-making process.

1. Introduction

The field of marine robotics has experienced significant advancements in recent years, with a focus on complex missions and the development of sophisticated acoustic networks (Zereik et al., 2018). These advancements have been supported by various guidance and control methodologies, including fuzzy-based and neural-network-based designs (Karimi and Lu, 2021). Systems engineering has been used to structure acquisition decisions for marine emission reduction technologies while taking stakeholder values and uncertainties into account (Aspen et al., 2018). The application of Multi-Criteria Decision Making (MCDM) in technology selection, particularly in the marine robotics field, is a critical need (Alam et al., 2021). MCDM methods, such as Genetic Algorithm (GA), Analytic Hierarchy Process (AHP) analysis, and Grey Relational Analysis–Technique for Order Preference by Similarity to Ideal Solution (GRA-TOPSIS), have been successfully applied in environmental decision-making (Azhar et al., 2021). The application of MCDM methods in the assessment of marine robotics technologies for mitigating marine oil spills and microplastic pollution is a relatively unexplored area (Onyena et al., 2021). The use of MCDM in risk assessment of marine technologies, such as Autonomous Underwater Vehicles (AUVs), has been demonstrated (Mohamed et al., 2023). However, the specific application of MCDM in marine robotics remains largely unexplored. The development of hybrid MCDM models, has shown promise in addressing decision-making problems (Goswami et al., 2021) and could be applied to the selection of

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marine robotics technologies. The review of MCDM methods by Sahoo and Goswami (2023) provides a comprehensive overview of the advancements and applications of these methods and highlights their potential in the field of marine robotics. This study aimed to address this gap by comparing three commonly used MCDM methodologies, GA, AHP, and GRA-TOPSIS with the new hybrid of the three GAGT to evaluate the suitability of marine robotics technologies for environmental mitigation purposes.

1.1 Marine Robotics Technology (MRT)

Marine robotics technologies (MRT), including Autonomous Underwater Vehicles (AUVs), Remotely Operated Vehicles (ROVs), and Unmanned Surface Vehicles (USVs), have undergone significant advancements in recent years. AUVs, specifically, have been the subject of research on improving navigation, localization, and control systems, as well as collaborative capabilities (González-García et al., 2020). Similarly, ROVs have been studied for their stability, control systems, and tether-management systems (Huvenne et al., 2018). The development of unmanned underwater vehicles (UUVs), including ROVs and AUVs, is driven by the need for repeated access to remote and hazardous places for data gathering and intervention (Petillot et al., 2019). Current research trends in AUVs include localization and navigation techniques, optimal path planning, and sensor technology (Sahoo et al., 2019). The design and control models of ROUVs have also been reviewed, with a focus on their applications and demand (He et al., 2020). The evolution of UUVs has been explored, including structural design, materials, sensors, actuators, and navigation control (Neira et al., 2021). The use of unoccupied aircraft systems (UASs) in marine science and conservation has been highlighted with a focus on their potential effects on marine wildlife (Johnston, 2019). Instrumentation and measurements in AUVs have been reviewed, with a focus on their future uses and development (Sanchez et al., 2020).

1.2 Selecting MRT for Oil Spill and Microplastic Mitigation

According to Copping et al., (2020), the key considerations when choosing MRT are versatility, efficiency, safety, and cost. A versatile MRT can handle different spills and pollution types, while an efficient MRT can quickly and effectively clean up spills without causing further harm. Safety is crucial, and cost is important; therefore, it is essential to choose a technology that offers value for money and long-term usability. These considerations are particularly important in the context of marine renewable energy (MRE) development, where the potential environmental effects and economic feasibility of the MRE are also significant factors (Bhuiyan et al., 2022). The impact of marine recreational fisheries (MRF) on fish stocks and ecosystems further underscores the need for effective, safe, and cost-efficient MRT (Lewin et al., 2019; Hyder et al., 2020). The development of scalable multi-vessel multi-float systems and the use of multi-target tracking technology for marine radar can contribute to achieving these goals (Chao and Yueji, 2020; D'Urso et al., 2021). The integration of MRE with ocean observations in a blue economy presents an opportunity to enhance the effectiveness and efficiency of MRT (Cavagnaro et al., 2020). Table 1 lists the key criteria and sub-criteria to be considered when selecting MRT for oil spill and microplastic mitigation. The alternatives listed in the table include AUVs, ROVs, USVs, Unmanned Underwater Gliders (UUGs), Glider, Wave Glider, BathyFloat, Saildrone, and Seaglider (Seegers et al., 2017). The sub-criteria for each key criterion include maneuverability, pollution handling capability, and adaptability for versatility; rate of change, sustainability, and reliability for efficiency; compliance, level of automation, and minimal risk for safety; and initial purchase cost, running cost, and funding options for cost. These sub-criteria are essential for making an informed decision when selecting MRT for oil spills and microplastic mitigation (Beaverson, 2015; Klein, 2021; Tikanmäki et al., 2021). Similarly, Table 2 presents the data on autonomous and unmanned vehicles used for oil spill cleanup. This includes information on oil types, spill sizes, primary cleanup methods, maximum oil encounter rates, and modifiers for oil type, spill size, and method. The vehicles listed are AUV, ROV, USV, UUV, UUGs, Wave Glider, BathyFloat, Saildrone, and Seaglider.

Table 1. Criteria and sub-criteria to consider when selecting MRT (Klein 2021; Tikanmäki et al.2021; Beaverson 2015; Jorge et al 2019; Hamurcu &Eren 2020; Jaurola et al., 2019).

Key Criteria	Sub-Criteria	Alternatives								
		AUV	ROV	USV	UUV	UUGs	Wave Glider	BathyFloat	Saildrone	Seaglider
Versatility	Maneuverability	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Pollution handling capability	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Adaptability	✓	✓	✓	✓	✓	✓	✓	✓	✓
Efficiency	Rate of change	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Sustainability	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Reliability	✓	✓	✓	✓	✓	✓	✓	✓	✓
Safety	Compliance	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Level of automation	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Minimal risk	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cost	Initial purchase cost	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Running cost	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Funding options	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2. Oil spill cleanup (Dave, 2011; Prendergast & Gschwend, 2014).

Oil Type	Primary Cleanup Method	Maximum Oil Encounter Rate	Oil Type Modifier (ti)	Spill Size Modifier (si)	Method	AUV	ROV	USV	UUV	UUGs	Wave Glider	BathyFloat	Saildrone	Seaglider
No.2 fuel	In-situ burning	18	0.18	2.00	0.25	✓	-	-	-	-	-	-	-	-
Light crude	Dispersants	160	0.32	0.65	0.46	-	-	-	-	-	-	-	-	-
Crude	Mechanical recovery	54	0.55	0.27	0.92	-	✓	✓	✓	✓	-	-	-	-
Heavy crude	-	-	0.65	0.15	-	-	-	-	-	-	-	-	-	-
No.6 fuel	-	-	0.71	0.05	-	-	-	-	-	-	-	-	-	-
No.4/5 fuel	-	-	1.82	0.0	-	-	-	-	-	-	-	-	✓	✓

2. Methodology

A comprehensive review of the literature on AUVs, ROVs, and USVs was conducted. This review is followed by a comparative analysis using the GA, AHP, and GRA-TOPSIS methodologies. AHP analysis was used to prioritize and weight criteria and sub-criteria, while GRA-TOPSIS analysis was employed to evaluate alternatives based on these criteria, which provided valuable insights for ranking the alternatives (Beskorovainyi, 2020). This approach aligns with the need for a method that combines different techniques to improve the efficiency of decision support systems (Beskorovainyi, 2020; Veerappan and Albert, 2020). Fig.1 illustrates the steps followed in this study.

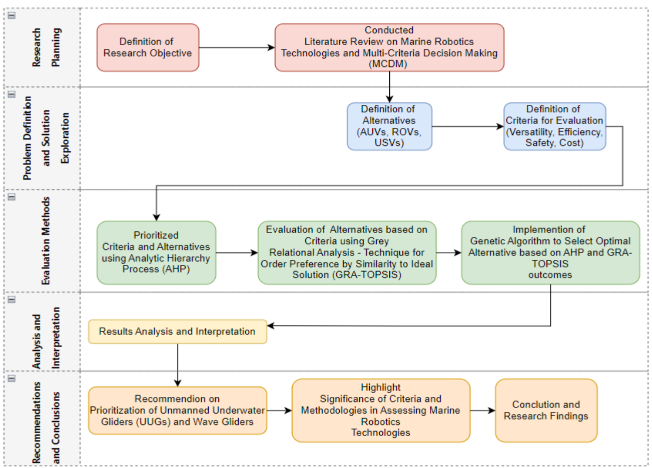

Fig. 1. Methodological steps.

2.1 Defining the alternative and criteria for evaluation

The effectiveness of MRT for oil spills and microplastic mitigation was assessed based on factors including versatility, efficiency, safety, and cost. Alternatives include AUVs, ROVs, USVs, UUGs, BathyFloats, Saildrones, and Wave Gliders, as shown in Fig. 2. The evaluation of MRT for combating marine oil spills and microplastic pollution involves key criteria, such as adaptability, efficiency, safety, and cost. Adaptability encompasses the ability to operate in diverse marine environments, perform a range of tasks, and integrate additional features (Zhang and Sun, 2024). Efficiency is determined by the energy consumption, speed, and payload capacity (Verfuss et al., 2019). Safety considerations include reliability, collision avoidance, and emergency response capabilities (Gallo et al., 2018). The cost is evaluated based on the initial investment, operational expenses, and long-term sustainability (Urbahs and Zavtkevics, 2020). These criteria are crucial for the successful deployment of marine robotics technologies to address environmental challenges.

2.2 Evaluation of MRT using AHP Analysis

The AHP analysis proposed by Saaty (1988) is another popular MCDM method that employs pairwise comparisons to derive the priority weights for each criterion and alternative. AHP's flexibility and ability of AHP to handle complex decision-making problems have led to its application in numerous domains such as renewable energy, transportation, and environmental conservation (Dinmohammadi and Shafiee, 2017). The procedure starts by describing the decision problem and building a hierarchy, followed by identifying the aim and appropriate criteria. A matrix was then used to perform pairwise comparisons to determine the relative importance of the criteria. To maintain consistency, the pairwise comparison matrix was normalized, and a weight vector was created to indicate the priority weights of the criteria or alternatives. A consistency check was performed to test the trustworthiness of the comparisons. Aggregation and ranking were performed using the overall priority weights, and sensitivity analysis was used to assess the robustness of the results (Sharma et al., 2020).

Step 1: Define the decision problem and establish the hierarchy.
Decision problem; Clearly articulate the decision problem and identify the goal. Hierarchy, identify criteria and subcriteria.
Step 2: Pairwise comparison.
Pairwise comparison matrix (X) as indicated in equation (1).

$$X = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mn} \end{bmatrix} \quad (1)$$

Step 3: Calculate normalized pairwise comparison matrix (Y) as shown in equation (2).

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \quad (2)$$

Step 4: Calculate weight vector (W).
The weight vector (W) can be calculated as indicated in equation (3)

$$w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \quad (3)$$

Step 5: Consistency check.
The consistency index (CI) and consistency ratio (CR) were calculated using Equations (4) and (5).

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (4)$$

$$CR = \frac{CI}{RI} \quad (5)$$

where CI represents the Consistency Index and RI is the Random Index.

Step 6: Aggregation and ranking.
The overall priority weights for the alternatives at the lowest level are calculated.

Step 7: Sensitivity analysis.
The robustness of the results is assessed, and the impact of parameter changes is evaluated.

2.3. Evaluation of the MRT using GRA-TOPSIS

The GRA is a versatile method that has been applied in various fields to evaluate relationships between different criteria or attributes. In the context of multi-criteria decision making, GRA has been integrated into the TOPSIS framework to rank alternatives based on their similarity to the ideal solution (Gugulothu et al., 2021). This approach has been used in a range of applications, including process parameter optimization in electrical discharge machining (Wu, 2021), oil spill emergency management (Zhang et al., 2021), teaching evaluation (Zakeri et al., 2022), sustainability assessment of hydrogen production technologies (Li et al., 2020), and predictive modeling of surface roughness (Hweju and Abou-El-Hossein, 2021). This method has also been extended to image recognition, where it has been shown to improve recognition speed and performance (Li et al., 2020). On the other hand, TOPSIS is a widely used MCDM method that ranks alternatives based on their relative closeness to an ideal solution and distance from a negative or anti-ideal solution (Quan et al., 2019; Wang et al., 2023). TOPSIS has been applied in various fields, including environmental management, to evaluate and select the best alternatives considering multiple conflicting criteria (Kacprzak, 2021).

The evaluation process begins by defining the criteria and assigning appropriate weights to each. A decision matrix consisting of strategies and criteria was then created. The decision matrix was normalized to ensure that all criteria were treated equally, facilitating comparisons between strategies. Grey relational coefficients were calculated to represent the degree of association between alternatives and criteria. Positive and negative ideal solutions were determined to assess the potential performance of each strategy (Jiang et al., 2010). Finally, the similarity to the positive ideal solution was calculated using the GRA-TOPSIS method, enabling the ranking of strategies based on their overall performance relative to the ideal solution.

Step 1: Define the evaluation criteria and weights. The evaluation criteria and their respective weights are represented as vectors as follows:

$$[w_1, w_2, \ldots, w_m] \tag{6}$$

where *m* is the number of evaluation criteria and w_i is the weight assigned to criterion *i*.

Step 2: Create a decision matrix with the alternatives and criteria.

Step 2 involves creating a decision matrix using MRT alternatives and criteria. Each alternative is assigned a score according to the criteria using a decision matrix (Liu et al., 2019; Wang et al., 2023). Decision matrix X is composed of m rows and n columns, where m represents the number of alternatives and *n* represents the number of criteria. Each matrix element A_{ij} indicates the evaluation of alternative A_i with criterion C_i. The greater the value of A_{ij}, the better the performance of alternative A_i concerning criterion C_j.

$$X = \{A_{ij}\} = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_m \end{array} \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mn} \end{bmatrix} \tag{7}$$

Step 3: Normalize the decision matrix.

The normalized decision matrix is calculated by dividing each element in the decision matrix by the sum of the corresponding column multiplied by its weight: Using for as indicated in the equation (8) and (9).

$$Y = \{y_{ij}\} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \tag{8}$$

Where;

$$y_{ij} = \frac{A_i}{\sum_1^m w_i A_{ij}} \quad \text{for } i = 1,2,\ldots,m \text{ and } j = 1,2,\ldots,n \tag{9}$$

Step 4: Determine Positive-Ideal Solution (PIS) denoted by Y^+ and the Negative-Ideal Solution (NIS) denoted by Y^-.The equations for calculating the PIS, $Y^+ = (y_1{}^+, y_2{}^+, \ldots, y_n{}^+)$ and NIS $Y^- = (y_1{}^-, y_2{}^-, \ldots, y_n{}^-)$ are as shown in equations (10) and (11).

$$y_j{}^+ = \max y_{ij} (i = 1,2,\ldots,m, j = 1,2,\ldots,n), \tag{10}$$

$$y_j{}^- = \min y_{ij} (i = 1,2,\ldots,m, j = 1,2,\ldots,n) \tag{11}$$

Step 5: Calculating the separation of each alternative from the PIS and NIS (Quan et al., 2019).

To determine how far apart each choice is from the PIS and NIS, the Euclidean distance is used, as indicated in equations (12) and (13).

$$D_j{}^+ = \|y_i - Y^+\|_2 = \sqrt{\sum_{j=1}^n \left(y_{ij} - y_j{}^+\right)^2} \quad (i = 1,2,\ldots,m) \tag{12}$$

$$D_j{}^- = \|y_i - Y^-\|_2 = \sqrt{\sum_{j=1}^n \left(y_{ij} - y_j{}^-\right)^2} \quad (i = 1,2,\ldots,m) \tag{13}$$

Where $D_j{}^+$ Represents the distance between alternatives y_i and Y^+ . $D_j{}^-$ represents the distance between alternatives y_i and Y^-.

Step 6: Estimation of grey relational coefficients.

Let PIS and NIS be the reference sequences, and each strategy can be determined. Then, the grey relation coefficients for each strategy to the PIS and NIS may be calculated by:

$$r_{ij}{}^+ = \frac{\min_i \min_j |y_j{}^+ - y_{ij}| + \zeta \max_i \max_j |y_j{}^+ - y_{ij}|}{|y_j{}^+ - y_{ij}| + \zeta \max_i \max_j |y_j{}^+ - y_{ij}|} = \frac{\zeta v_j}{v_j - y_{ij} + \zeta v_j} \quad (i = 1,2,\ldots,m, j = 1,2,\ldots,n) \tag{14}$$

$$r_{ij}{}^- = \frac{\min_i \min_j |y_j{}^- - y_{ij}| + \zeta \max_i \max_j |y_j{}^- - y_{ij}|}{|y_j{}^- - y_{ij}| + \zeta \max_i \max_j |y_j{}^- - y_{ij}|} = \frac{\zeta v_j}{v_j - y_{ij} + \zeta v_j} \quad (i = 1,2,\ldots,m, j = 1,2,\ldots,n) \tag{15}$$

where ζ is the distinguishing coefficient, $\zeta \in [0, 1]$; $\zeta = 0.5$ is usually applied following the rule of least information.

Step 7: Calculate the consolidated results and grey relational degree.

$$r_{ij}{}^+ = \frac{1}{n} \sum_{j=1}^n r_{ij}{}^+ (i = 1,2,\ldots,m), \tag{16}$$

$$r_{ij}{}^- = \frac{1}{n} \sum_{j=1}^n r_{ij}{}^- (i = 1,2,\ldots,m), \tag{17}$$

Equations (11) and (12) are used to execute $D_i{}^+$, $D_i{}^-$, $r_i{}^+$and $r_i{}^-$ dimensionless processing on and generate integrated results.

$$q_i{}^+ = \beta \frac{D_i{}^+}{\max(D_i{}^+)} + \gamma \frac{r_i{}^+}{\max(r_i{}^+)} \quad (i = 1,2,\ldots,m) \tag{18}$$

$$q_i{}^- = \beta \frac{D_i{}^-}{\max(D_i{}^-)} + \gamma \frac{r_i{}^-}{\max(r_i{}^-)} \quad (i = 1,2,\ldots,m) \tag{19}$$

where β is a measure of how closely an alternate solution comes to the ideal option in terms of proximity. γ represents the closeness's influence on the grey relational degree of the ideal and alternate solutions. $\beta, \gamma \in [0, 1]$, $\beta + \gamma = 1$.

Step 8: Calculate and grade the options' closeness (Quan et al., 2019).

$$C_i = \frac{q_i^+}{q_i^+ + q_i^-} \; (1,2, \dots, m) \tag{20}$$

Closeness is specified to establish the ranking order of all options. The closeness coefficient compares an option's proximity to the positive ideal solution with its proximity to the negative ideal solution. A greater C_i value suggests a closer match to the positive ideal solution.

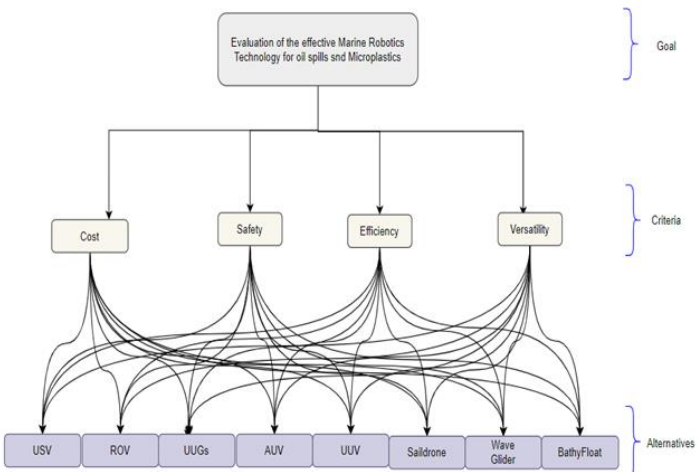

Fig. **2**. Defining the alternative and criteria for evaluation.

2.4 Evaluating MRT using GA

A range of studies have demonstrated the versatility and effectiveness of GA in addressing complex decision-making problems. Ntakolia et al., (2022) applied a fuzzy Genetic Algorithm to optimize maritime operations, whereas Shafiei et al., (2021) extended this methodology to mixed uncertain problems. Both studies successfully addressed conflicting goals in planning natural gas and petroleum transportation. Mohammad-Azari Bozorg-Haddad and Loáiciga (2020) reviewed the state-of-the-art of Genetic Programming (GP) in water-resources systems analysis, highlighting its capability and superiority. Moreover, Vié (2020) discussed the qualities, challenges, and future of GAs, emphasizing their computational efficiency and the need for further innovation. Alam-Mohammad and Hira (2021) explored the role of GAs in engineering pedagogies and their applications in solving complex problems. These studies collectively underscore the potential of GAs and GPs to address a wide range of decision-making problems (Fig. 3).

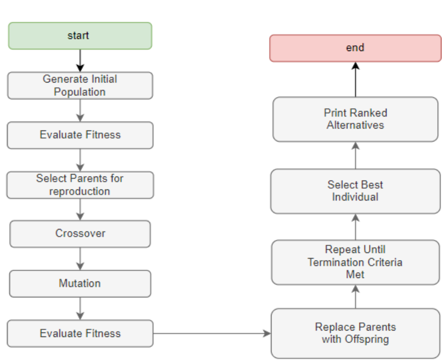

Fig. **3**. Genetic algorithm steps.

3. Results and Discussion

One of the aims of this study was to assess the effectiveness of marine robotics technologies in combating marine oil spills and microplastic pollution using multi-criteria decision-making methods such as genetic algorithms, analytic hierarchy processes, and grey relational analysis. This study compared various marine robotics technologies based on key criteria, including adaptability, efficiency, safety, and cost. After applying these methods, the following results were obtained.

3.1 AHP analysis

The criteria weights and alternative scores provided in the table were derived from a group decision-making session involving five individuals from East Africa who possessed a deep understanding of marine robotics for marine oil spill and microplastic mitigation. These individuals are considered experts in multi-criteria decision-making processes within this domain. Through collaborative discussions and deliberations, the group collectively assigned weights to criteria, such as versatility, efficiency, safety, and cost, reflecting their relative importance in evaluating the effectiveness of marine robotics technologies. Likewise, they assessed the performance of various alternatives, including AUVs, ROVs, USVs, UUVs, UUGs, BathyFloats, Saildrones, and Wave Gliders, based on their expertise and knowledge. The resulting scores represent a consensus reached through the integration of diverse perspectives and expertise in the field, as indicated in Table 3 and Table 4.

Table 3. Criteria weights.

Criteria	Weight
Versatility	8.73
Efficiency	52.12
Safety	16.00
Cost	23.14

Table 4. Score of alternatives against the criteria.

Alternative	AUV	ROV	USV	UUV	UUGs	Bathy Float	Saildrone	Wave Glider
Versatility	7	8	7	7	6	8	7	6
Efficiency	6	8	8	6	6	6	6	5
Safety	8	8	8	8	7	8	9	8
Cost	6	6	8	6	6	7	6	4

Table 5 displays the final ranked scores of the alternatives for marine oil spills and microplastic mitigation. The USV tops the list with a score of 0.1325, followed closely by a ROV with a score of 0.1304. The UUGs ranked third with a score of 0.1279. Similarly, AUVs and UUVs share the fourth position with a score of 0.1232. The saildrone, wave glider, and bathyfloat follow suit with decreasing scores. In addition, the sensitivity analysis of the output results involves examining how changes in criteria weights impact the final scores of the alternatives (Fig. 4). By adjusting the weights assigned to criteria such as versatility efficiency, safety, and cost, stakeholders can observe shifts in the rankings of alternatives cost.

Table 5. Final ranked scores of alternatives.

Rank	Alternative	Final Ranked Score
1	USV	0.1325
2	ROV	0.1304
3	UUGs	0.1279
4	AUV	0.1232
5	UUV	0.1232
6	Saildrone	0.1218
7	Wave Glider	0.1205
8	BathyFloat	0.1204

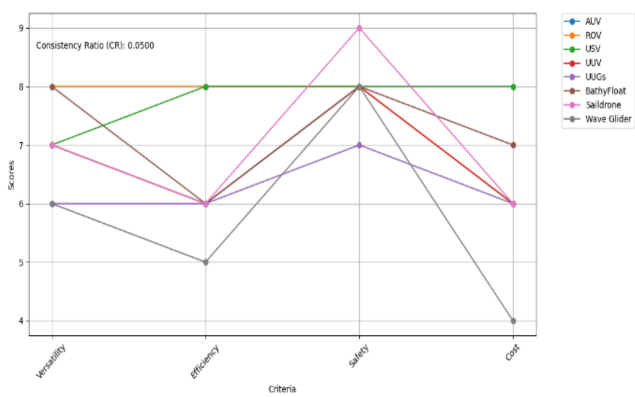

Fig. 4. Sensitivity analysis of alternatives against criteria.

3.2. GRA-TOPSIS analysis

Table 6 presents a normalized decision matrix depicting the performance of various marine robotic alternatives across four criteria: versatility, efficiency, safety, and cost. From the findings;

- *i)* *ROV and USV emerge as top performers in terms of efficiency and safety, while saildrones lead to safety.*
- *ii)* *AUV and UUV exhibit cost-effectiveness.*
- *iii)* *Versatility varies among the alternatives, with ROV showing strong performance.*
- *iv)* *ROV stands out as a robust choice across multiple criteria, while AUV and UUV offer cost-effective options. The choice of the most suitable alternative depends on the specific priorities and trade-offs concerning the importance of each criterion.*

Table 6. Normalized decision matrix.

	Versatility	Efficiency	Safety	Cost
AUV	1.09125	6.13176471	2	2.83346939
ROV	1.24714286	8.17568627	2	2.83346939
USV	1.09125	8.17568627	2	3.77795918
UUV	1.09125	6.13176471	2	2.83346939
UUGs	0.93535714	6.13176471	1.75	2.83346939
BathyFloat	1.24714286	6.13176471	2	3.30571429
Saildrone	1.09125	6.13176471	2.25	2.83346939
Wave Glider	0.93535714	5.10980392	2	1.88897959

In addition, Table 7 presents the best and worst achievable performance levels across the criteria, respectively. PIS indicates the optimal performance that an alternative can attain, whereas NIS represents the least desirable performance.

Table 7. Positive ideal solution and negative-ideal solution.

	Versatility	Efficiency	Safety	Cost
PIS	1.24714286	8.17568627	2.25	3.77795918
NIS	0.93535714	5.10980392	1.75	1.88897959

Similarly, Table 8 indicates how each alternative's performance deviates from the best and worst possible scenarios, respectively. Higher Dj+ values suggest a greater distance from optimal performance, whereas lower Dj- values imply better performance relative to the worst-case scenario.

Table 8. Separation from PIS and NIS.

Alternatives (Options)	Dj+	Dj-
AUV	2.27078818	1.42241604
ROV	0.97701636	3.23286342
USV	0.29462278	3.61312622
UUV	2.27078818	1.42241604
UUGs	2.32742061	1.39156919
BathyFloat	2.11261227	1.79199648
Saildrone	2.25698448	1.48686496
Wave Glider	3.62320146	0.25

In addition, the grey relational coefficients (r+) and (r-) (Table 9) provide a comparative analysis of each alternative's performance relative to the positive-ideal and negative-ideal solutions, respectively. Higher rj+ values indicate closer proximity to the positive-ideal solution, implying better overall performance, whereas lower rj- values suggest less similarity to the negative-ideal solution, indicating superior performance relative to the worst-case scenario.

Table 9. Grey relational coefficients (r+) and (r-).

Alternatives (Options)	r+	r-
AUV	1.81538404	1.81538404
ROV	2.0	1.66197087
USV	1.81538404	1.66197087
UUV	1.81538404	1.81538404
UUGs	1.66197087	2.0
BathyFloat	2.0	1.66197087
Saildrone	1.81538404	1.81538404
Wave Glider	1.66197087	2.0

Likewise, the consolidated results (q+) indicate the overall performance of the alternatives relative to the positive-ideal solution, with the USV showing the highest performance. Conversely, the grey relational degree (q-) highlights how alternatives perform relative to the negative-ideal solution, with Wave Glider demonstrating the best performance. Table 10 represents the results of calculating the consolidated results (q+) and grey relational degree (q-) for each alternative (AUV, ROV, USV, UUV, UUGs, BathyFloat, Saildrone, Wave Glider), providing insights into their overall performance based on the GRA.

Table 10. Consolidated results (q+) and grey relational degree (q-).

Alternatives (Options)	r+	r-
AUV	1.40740406	1.49311834
ROV	1.73927233	1.32143172
USV	1.88373714	1.27439221
UUV	1.40740406	1.49311834
UUGs	1.3161851	1.60938121
BathyFloat	1.52642096	1.40523293
Saildrone	1.47751293	1.44025268
Wave Glider	1.23603892	1.92989113

On the other hand, the closeness of options values (Table 11) indicates how closely each alternative aligns with the ideal solution, with Wave Glider showing the highest performance and USV exhibiting the lowest. These results offer a snapshot of each alternative's relative effectiveness, guiding decision makers in understanding their strengths and areas for improvement.

Table 11. The closeness of each alternative to the ideal solution.

Alternatives (Options)	(Ci)
AUV	0.54063172
ROV	0.4302945
USV	0.39440183
UUV	0.54063172
UUGs	0.52382862
BathyFloat	0.53233705
Saildrone	0.54862863
Wave Glider	0.60768706

3.2.1. Finding after performing GRA-TOPSIS analysis

The findings reveal the following rankings based on the comprehensive performance index (Ci) derived from the GRA and the TOPSIS for alternatives aimed at combating marine oil spills and microplastic pollution. These rankings highlight Wave Glider as the top-performing alternative, followed by Saildrone, AUV, UUV, BathyFloat, UUGs, ROV, and USV, indicating their effectiveness in addressing marine pollution challenges. The effectiveness of the GRA-TOPSIS method in addressing marine pollution challenges has been demonstrated in various studies. Lu et al., (2022) and Mollaoglu et al., (2023) both use the method to optimize engine settings and evaluate fuel alternatives, respectively, for reducing emissions. Petrovic et al., (2023) applied this method to marine vessel classification and trajectory forecasting, while Zhou et al., (2021) used it for sustainable product design.

3.3 Genetic Algorithm Analysis

According to the implemented genetic algorithm for selecting the optimal alternative based on the average outcomes of AHP and GRA TOPSIS, as indicated in, a population size of 100 individuals was utilized over a span of 100 generations. A mutation rate of 0.1 was applied to introduce variability, while parent selection involved tournaments comprising five individuals. The algorithm randomly selects crossover points within the individual chromosomes to facilitate recombination. Termination was triggered when the maximum number of generations was reached. Ultimately, the best individual, characterized by the highest fitness score, was identified, leading to the ranking of alternatives based on their respective fitness scores, as indicated in Table 12.

Table 12. Average results of AHP and GRA TOPSIS analysis.

Alternative	AHP Results	GRA-TOSPIS Results	Average (AHP & GRA-TOPSIS)
USV	0.1325	0.39440183	0.263450915
ROV	0.1304	0.4302945	0.28034725
UUGs	0.1279	0.52382862	0.32586431
AUV	0.1232	0.54063172	0.33191586
UUV	0.1232	0.54063172	0.33191586
Saildrone	0.1218	0.54862863	0.335214315
Wave Glider	0.1205	0.60768706	0.36409353
BathyFloat	0.1204	0.53233705	0.326368525

After running the GA as indicated in Table 13 based on the combined results of the AHP and the GRA-TOPSIS. UUGs emerged as the best alternative with a score of 0.6133, outperforming the others. Decision makers can prioritize UUGs owing to their superior performance. However, Wave Glider follows closely, suggesting that it is a competitive alternative. The other options had lower scores, indicating inferior performance. Hence, UUGs stand out as the preferred choice based on this analysis.

Table 13. GA results.

Alternative	GA Results
USV	0.5000
ROV	0.4974
UUGs	0.6133
AUV	0.4585
UUV	0.4585
Saildrone	0.4194
Wave Glider	0.5041
BathyFloat	0.3234

The comparison of the results for different alternatives using AHP, GRA-TOPSIS, and GA provides valuable insights into their performance across various evaluation criteria (Fig. 5). Each method offers unique perspectives, allowing decision makers to comprehensively assess alternatives.

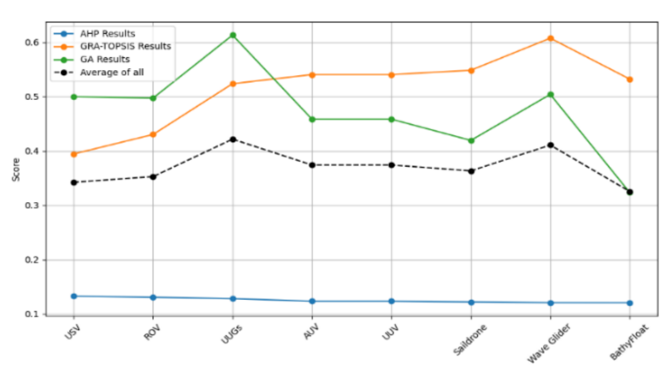

Fig. 5. Comparison of results for different alternatives.

3.4 Summary of the key findings

The analysis of underwater glider (UG) performance reveals that UUGs are the top alternative, as determined by a GA (Wang et al., 2021). The Wave Glider also demonstrated strong performance across both GRA-TOPSIS and GA, indicating its competitiveness (Yang et al., 2020). Decision-makers are advised to integrate multiple evaluation techniques to make well-informed decisions (Chen et al., 2018). The application of the Success-History Based Adaptive Differential Evolution Algorithm (SHADE) to underwater glider path planning (UGPP) is found to yield stable and competitive output trajectories (Zamuda and Sosa, 2019). The proposed variable-structure filtering method for an unmanned wave glider (UWG) was shown to be feasible and suitable for high sea conditions (Yiming et al. 2021). A review of underwater gliding robots (UGRs) provides valuable insights into their development and future potential (Wang et al., 2022). Sensitivity analysis and parameter optimization of energy consumption for UGs highlight the importance of the gliding angle, velocity, diving depth, and drag coefficient (Song et al., 2020).

4. Conclusion

The objective of this study is to evaluate the effectiveness of various marine robotics technologies in addressing marine oil spillage and microplastic pollution. Using multi-criteria decision-making methods such as GA, AHP, and GRA-TOPSIS, the study successfully assessed and ranked marine robotics technologies based on key criteria, including versatility, efficiency, safety, and cost. The analysis revealed that UUGs emerged as the top-performing alternative, closely followed by the Wave Glider. Sensitivity analysis further confirmed the robustness of these rankings, highlighting the significance of the criteria weights in determining the performance of the technologies. Despite the valuable insights gained from this study, it is important to acknowledge its limitations. This research focused primarily on the effectiveness of marine robotics technologies in addressing oil spills and microplastic pollution, potentially overlooking other environmental challenges. The findings of this study are based on specific criteria and may not encompass all aspects of technology performance. The study recommends prioritizing the implementation and advancement of UUGs and wave gliders for managing marine oil spills and microplastic pollution. The use of UUGs and Wave Gliders has been recommended for managing marine oil spills and microplastic pollution because of their superior performance and effectiveness (Maawali et al., 2019; Bayırhan and Gazioğlu, 2020; Massari et al. 2023). These technologies have demonstrated superior performance and effectiveness in the preservation of marine ecosystems. Future research endeavors and investments should concentrate on optimizing and enhancing the capabilities of UUG and Wave Glider to bolster their roles in combating environmental threats in marine environments.

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