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Determining the Optimal Selection Criteria for Unmanned Surface Vehicles in Port Security Using Fuzzy AHP and the Best-Worst Method

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ABSTRACT

The primary objective of this study is to evaluate the selection criteria for unmanned maritime vehicles in the context of port security. The selection criteria were obtained through a comprehensive review of the extant literature and consultation with experts in the field. The objective was to ascertain the relative weights of these criteria using the fuzzy AHP and Best Worst Method. The evaluations of five decision makers were utilised in the implementation phase. Following a thorough evaluation of the available data, it was determined that both methods yielded analogous results. The most significant criteria was determined to be "Endurance," while "Maintenance Cost" and "Investment Cost" were found to be of lesser importance. The study provides port operators with a unique perspective on the use of unmanned maritime vehicles for port security, emphasising the criteria that should be given greater attention.

1. Introduction

Ports, which are at the center of globalizing trade networks, are not only one of the fundamental components of economic development but also have critical importance at national and international levels with their strategic, environmental and security dimensions. Especially in the United States, the security of port facilities has become an element of political interest due to the increasing threat of terrorism after the 9/11 attacks [1].

Since most of the goods are transported by ships today, ports are key national infrastructures. Ports are not only the centers of economic activities but also strategically important structures for national security. The security of port infrastructure faces multifaceted and complex maritime security threats such as illicit trade, terrorism, cyber-attacks, environmental threats and transnational illegal activities (human trafficking, migrant smuggling, trafficking of weapons of mass destruction (WMD) etc.). Considering the increasing international trade volume, energy transportation and the concentration of critical infrastructures, it is emphasized that more attention

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should be paid to port security vulnerabilities. This situation requires continuous surveillance operations, advanced environmental awareness, threat detection and rapid response capabilities in port areas. In this context, the integration of innovative and autonomous technologies has become critically important in addition to traditional security methods. In this context, this article focuses on determining the optimal selection criteria for unmanned surface vehicles (USVs) in port security.

The history of maritime vessels is as old as human history itself, due to the fact that two-thirds of the Earth's surface is covered by water [2]. Some of the water bodies on earth can be explored with traditional manned sea vehicles, but with the increasing population, the need to explore large water bodies that are either too risky or too costly to explore with manned vehicles has become inevitable. [3]. Significant research and development efforts have been devoted to unmanned underwater vehicles (UUVs) and unmanned aerial vehicles (UAVs); however, USVs, also known as autonomous surface vehicles, have remained relatively underexplored [4].

Although the history of USVs dates to World War II, the projects only became widespread in the 1990s [5]. With the development of technology, unmanned vehicles have improved in terms of safety, usability and cost, creating a significant increase in commercial and civilian use opportunities [1]. USVs offer a wide range of applications and represent a technology in high demand in today's rapidly evolving era [6].

The term USV refers to any vehicle operating on the surface of the water without a crew. In other words, USVs are autonomous or remotely controlled marine vehicles operating on the surface of the water without a human crew. These vehicles are equipped with various sensors, communication systems and sometimes weapon systems and can perform a wide range of tasks from reconnaissance and surveillance to environmental monitoring and mine detection. USVs can be deployed from ships, submarines or coastal facilities and perform tasks such as maritime surveillance, anti-submarine warfare (ASW), search and rescue operations and even offensive attacks against enemy ships or coastal targets. The use of USVs not only reduces the likelihood of marine accidents but also offers advantages such as lower operational costs (including crew expenses) and reduced fuel consumption. These vehicles, which have a wide range of applications, offer the potential to reduce accident risks associated with collisions, grounding, and stranding incidents and maritime security threats through effective analysis [6, 7].

Moreover, USVs have been found to possess the potential—and in some cases, demonstrated capability—to reduce risks to manned forces, provide the necessary force multiplication for conducting military operations, perform tasks that manned platforms cannot, and do so in a cost-effective manner for naval forces [4]. Although extensive studies have been conducted, there is little established best practice in the application of USVs to port security. The development of USVs is a notable trend in naval warfare and maritime security [6]. Therefore, the selection of USVs for use specifically in port security holds significant importance in literature.

The primary objective of this article is to identify the criteria that should be considered in the selection of USV systems for port security and to systematically determine the relative importance of these criteria. To achieve this goal, two complementary multi-criteria decision-making methods were employed: the Fuzzy Analytic Hierarchy Process (Fuzzy AHP), which allows for the expression of decision-makers' subjective judgments under uncertainty, and the Best-Worst Method (BWM), developed to enhance the consistency of decisions. The combined use of these methods enhances the reliability, flexibility, and consistency of the decision-making process under uncertainty. The outcome of this article aims to provide a systematic reference for technological investment decisions in port security and to offer a methodological contribution to the evaluation processes of public and private sector actors involved in selecting USV systems. In this regard, the proposed model is expected to support decision-making processes in security-oriented port management and serve as a foundation for advanced strategic analyses.

The remainder of this study is organized as follows: Section 2 presents the literature review. Section 3 defines the problem and explains the rationale and motivation behind the study. Section 4 outlines the application steps of the proposed the Fuzzy AHP technique and BWM. In Section 5, participant information related to the study is provided, the results obtained from participants are presented, and a comparative analysis of the two employed methods is included. In Section 6, the results and findings are explained and interpreted. The section concludes with a general evaluation and conclusion of the study, which is discussed within the context of the findings.

2. Literature Review

Multi-Criteria Decision Making (MCDM) techniques are effective tools that are utilized in the selection of the optimum criteria in complex decision-making processes. In MCDM problems, it has been demonstrated that criteria weights are one of the key elements that can significantly affect the results [8]. Consequently, researchers have developed various methods to determine criteria weights. The following studies are cited in the relevant literature.

In his study, Ozcalici [9] investigated the effect of criteria weights on portfolio return in detail. The weights of the criteria were determined by four different CRA weighting techniques (CILOS, CRITIC, MEREC and SECA). The effect of these weights on the performance of 17 CRA techniques (ARAS, CoCoSo, CODAS, COPRAS, EDAS, GRA, MABAC, MAIRCA, MARCOS, MOORA, MOOSRA, OCRA, SAW, TODIM, TOPSIS, VIKOR, WASPAS) was examined.

In their seminal work, Zavasdaskas and Podvezko [10] synthesized the most salient features of the entropy method and the CILOS approach, thereby developing a novel methodology they termed Integrated Determination of Objective Criteria Weights (IDOCRIW). This approach was employed in the context of criteria weighting.

In their study, Gurler et al. [11] present a logistics performance evaluation model in which criteria weights are determined by GA. In this study, 11 techniques were used to determine the logistics performance of EU countries across 33 indicators.

Keshavarz-Ghorabaee et al. [12] introduced a new method to the literature by using a new method called MEREC (Method Based on the Lift Effects of Criteria) to determine the objective weights of criteria.

In his study, Ginevičius [13] utilized a new method called FARE (Factor Relationship) to determine criteria weights. FARE involves obtaining preliminary data from experts on the relationships between various criteria.

Žižović and Pamucar [14] used the Level-Based Weight Assessment (LBWA) model in their study, which includes steps such as determining the most important criterion, grouping criteria according to their importance, comparing criteria within these groups, and calculating weighting coefficients.

In their article, Kobryń [15] proposed using the DEMATEL method to determine criteria weights.

Stanujkić and colleagues [16] propose two extensions of the SWARA method to determine the weights of evaluation criteria in situations where consensus is difficult to achieve.

Kolios and colleagues [17] used the WSM, WPM, TOPSIS, AHP, ELECTRE, and PROMETHEE methods to determine criteria weights.

In their study, Altundas et al. [18] sought to ascertain the optimal UAV ranking for a specific mission. The criteria employed in the study were evaluated in conjunction with UAV experts and categorized under eight primary headings. Pairwise comparisons were conducted to determine the relative importance of the criteria, with the weights assigned to each criterion determined by the AHP method. The ranking and selection of UAVs was conducted utilizing the ARAS, EDAS and WASPAS methods, which have recently emerged in the extant literature, and MAUT, TOPSIS and VIKOR methods, which are frequently employed in the literature.

Selecting the most appropriate security measures for ports and unmanned vehicles is a complex decision-making process that can benefit from multi-criteria decision analysis methods. The literature on unmanned surface vehicles (USVs) has expanded significantly, addressing various aspects of their applications in maritime environments, particularly in security contexts.

Hozairi et al. [19] present a hybrid fuzzy-AHP TOPSIS approach for selecting the most appropriate maritime security policy for Indonesia.

Nichols et al. [20] lay the groundwork by discussing the operational advantages of USVs, such as their durability and energy efficiency, and by emphasizing the need to select the most appropriate criteria for their deployment in security scenarios.

Xin et al. [21] present innovative optimization strategies that demonstrate the importance of multi-sensor fusion for real-time navigation. Their findings on particle swarm optimization contribute to the understanding of path efficiency and resource management in USV operations, reinforcing the importance of selecting appropriate criteria for navigation and operational success.

This study aimed to determine the best selection criteria for unmanned surface vehicles in port security using fuzzy AHP and the BWM.

3. Problem Definition

As discussed in previous sections, this study focuses on weighting criteria for unmanned surface vehicles (USVs) in the context of port security. The aim is to inform the decision-making process by establishing the weighting of the criteria before the selection phase begins. The Fuzzy AHP and Best Worst Methods were employed to determine the importance weights of these criteria. Information regarding these nine criteria is provided below. A total of nine criteria were identified as follows.

C_1*: Endurance*
This term refers to the USV's structural and functional durability under different sea states, including rough waters, high waves, wind conditions, and changing maritime situations. A high level of endurance is therefore essential for the USV to maintain operational stability and performance in adverse weather and sea conditions, which is vital for ensuring uninterrupted port surveillance and security operations.
C_2*: Range:*
This parameter delineates the maximum operational distance at which the USV is capable of operating from its base or control center, while ensuring the maintenance of control, communication, and mission effectiveness. The augmentation of range facilitates the surveillance of more expansive areas, thereby enhancing the efficacy of the USV in large port areas characterized by intricate geography.
C_3*: Operational Speed*
This parameter is indicative of the typical cruising and maximum speed at which the USV can navigate during missions. The enhanced operational speed of the system facilitates expeditious deployment, accelerated mission execution, and superior responsiveness in scenarios where time is of the essence, such as intruder detection or emergency response in maritime security contexts.
C_4*: Payload Capacity*

This term refers to the maximum weight and volume of equipment, sensors, or mission-specific tools that the USV can carry without compromising performance. A higher payload capacity facilitates the integration of advanced surveillance systems, communication tools, or defensive equipment, thereby enhancing mission versatility.

C_5: Sensors System

The suite of onboard sensory technologies is comprised of electro-optical/infrared (EO/IR) cameras, radar, sonar, and environmental monitoring sensors. A sophisticated sensor system enhances the USV's ability to detect, identify, and track potential threats or anomalies within port areas, contributing to effective situational awareness.

C_6: Data Security

The process entails the safeguarding of sensitive data collected, processed, and transmitted by the USV during its missions. This encompasses encryption techniques, secure communication protocols, and cybersecurity measures designed to prevent unauthorized access, data breaches, or cyberattacks that could compromise mission integrity or port security.

C_7: Navigation System

This term refers to the onboard navigational technologies that enable precise movement, positioning, and route planning of the USV. This encompasses GPS, inertial navigation systems (INS), and autonomous path planning algorithms. A reliable navigation system is critical for obstacle avoidance, mission accuracy, and safe operation in congested or restricted maritime zones.

C_8: Maintenance Cost

This figure is intended to represent the anticipated cost of regular upkeep, part replacements, and technical servicing throughout the USV's operational life cycle. Reduced maintenance requirements and costs are advantageous as they decrease the total cost of ownership and enhance operational readiness.

C_9: Investment Cost

This cost encompasses the total financial obligation incurred at the outset for the acquisition and implementation of the USV, inclusive of the expenses associated with the platform, sensor integration, control systems, and any essential infrastructure. This criterion assumes particular significance for stakeholders operating within budgetary constraints, as it exerts a pivotal influence on the decision-making process concerning procurement.

The criteria of the study and the criteria definition table are illustrated in Fig. 1.

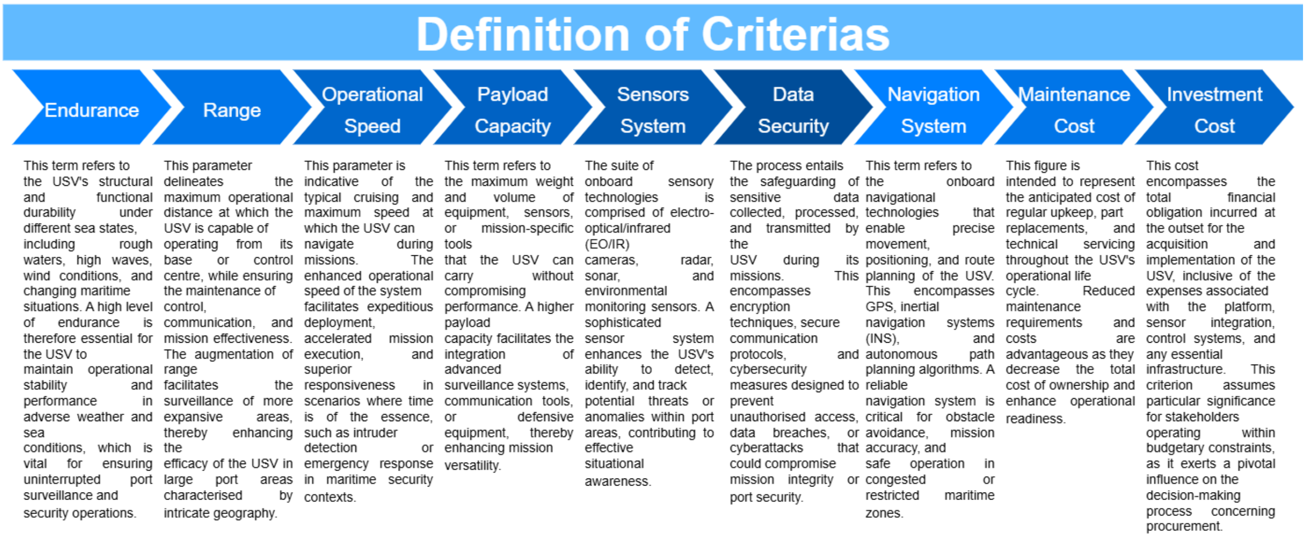

Fig. 1. Definition of criteria.

4. Methodology

MCDM is a popular method frequently employed to solve problems by implementing a variety of techniques, one of which is AHP. AHP is a calculation method that involves the structuring of complex problems into a hierarchical order. The application can also be used to select the most suitable criteria with high priorities, taking into account other factors [22].

The theory of fuzzy logic was introduced by Dr. Lotfi Aliasker Zadeh in 1965. Unlike classical Aristotelian logic, which often fails to provide complete or precise solutions in complex real-life situations, fuzzy logic offers a framework based on fuzzy sets and fuzzy numbers to handle ambiguity more effectively.

The application areas of fuzzy logic are very wide. Its biggest benefit is that it allows the "human-specific learning through experience" phenomenon to be easily modeled and that even vague concepts can be expressed mathematically [23].

4.1 Fuzzy AHP

It is evident that a considerable proportion of real-life decision-making scenarios are characterized by a degree of ambiguity and uncertainty. Consequently, solution methods that can overcome uncertainty should be favored in the resolution of such problems [24]. The development of fuzzy set theory was pioneered by Zadeh. In accordance with fuzzy theory, it is more accurate to evaluate key expressions in human thought with verbal expressions rather than numerical expressions. Furthermore, it is possible to quantify verbal expressions with fuzzy set values [25].

In the extant literature, triangular fuzzy number values are generally employed due to their ease of use and computation. The values of the triangular fuzzy number $\tilde{M}$ are expressed by the symbols (l, m, u). Within this framework, "l" denotes the lowermost threshold, "m" signifies the uppermost threshold, and "u" represents the upper limit. The membership function of the triangular fuzzy number $\tilde{M} = (l, m, u)$ is as follows [26].

$$\mu_{\widetilde{M}}(x) = \begin{cases} 0 & x < l \\ (x-l)/(m-l) & l \leq x \leq m \\ (u-x))/((u-m) & m \leq x \leq u \\ 0 & x > u \end{cases}$$

Within the scope of the Fuzzy AHP method, which has more than one approach, Chang's approach was used for calculations in this study.

The fuzzy AHP method has the capacity to incorporate verbal evaluations into the problem, in contrast to the classical AHP method, and can more effectively reflect the ambiguity of verbal expressions in the solution. In fuzzy AHP, pairwise comparisons are made with verbal expressions that can be expressed by fuzzy numbers. Consequently, decision makers are able to articulate the relative importance of two variables in relation to each other through the utilization of fuzzy set verbal values. As given in Table 1 [27], the fuzzy AHP importance scale was developed for the purpose of transforming verbal expressions into fuzzy numbers [28].

Table 1
Fuzzy AHP importance scale

Explanation	Importance Rating	Importance Rating Equivalent
Equally Important	(1,1,1)	(1,1,1)
More Important	$(2/3, 1, 3/2)$	$(2/3, 1, 3/2)$
Much More Important	$(3/2, 2, 5/2)$	$(2/5, 1, 2/3)$
Extremely Important	$(5/2, 3, 7/2)$	$(2/7, 3, 2/5)$
Definitely Important	$(7/2, 4, 9/2)$	$(2/9, 4, 7)$

The following section outlines the application steps of the Fuzzy AHP method employed in the present study [24].

The initial step in the process is to calculate the fuzzy synthetic order value for each pair-wise comparison. The fuzzy synthetic order value of criterion i is calculated with the help of Eq. (1).

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} \tag{1}$$

In order to calculate the value of $\sum_{j=1}^{m} M_{gi}^{j}$ in Eq. (1), the fuzzy sum operation on the value of m is calculated as in Eq. (2) for a given matrix.

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j , \sum_{j=1}^{m} m_j , \sum_{j=1}^{m} u_j\right) \tag{2}$$

In order to obtain the $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]^{-1}$ expression, the fuzzy aggregation process is performed with the $M_{gi}^{j} (j = 1,2, \dots \dots, m)$ values, and the inverse of the vector in the equation given in Eq. (3) is calculated as in Eq. (4).

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{i=1}^{n} l_i , \sum_{i=1}^{n} m_i , \sum_{i=1}^{n} u_i\right) \tag{3}$$

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m}M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n}u_i},\frac{1}{\sum_{i=1}^{n}m_i},\frac{1}{\sum_{i=1}^{n}l_i}\right) \tag{4}$$

The following text is intended to provide a comprehensive overview of the subject matter. In the second step of the process, the degrees of likelihood are calculated in order to establish a ranking of the fuzzy synthetic order values (M_i). At this juncture, in accordance with the methodology established by Chang [28], the comparison of two distinct synthetic order values, $M_1 = (l_1, m_1, u_1)$, is undertaken. In the circumstance where $M_2 = l_2$, It can be demonstrated that M_2 and u_2 are two distinct triangular fuzzy numbers. The degree of likelihood that $M_2 = (l_2, m_2, u_2)$ is greater than $M_1 = (l_1, m_1, u_1)$ is expressed as in Eq. (5).

$$V(M_2 \geq M_1)\mu_{M1}(d) = \begin{cases} 1 & if\ m_2 \geq m_1 \\ 0 & ,\ if\ l_1 \geq u_2 \\ (l\_1 - u\_2)/((m\_2 - u\_2) - (m\_1 - l\_1)) & otherwise \end{cases} \tag{5}$$

The value of d in Eq. (5) is defined as the ordinate of the highest intersection point between μ_{M1} and μ_{M2}, as illustrated in Eq. (6) below.

$$V(M_2 \geq M_1) = hight(M_1 \cap M_2) = \mu_{M1}(d) \tag{6}$$

Moreover, in order to draw parallels between the values of M_1 and M_2, it is necessary to ascertain the values of $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ despite the fact that the method developed by Chang [28] has been extensively utilized in the extant literature, it is not without its drawbacks. As posited by Wang et al. [29], the synthetic values calculated by means of the method proposed by Chang [28] are only commensurate with two triangular fuzzy numbers. The values thus calculated are inadequate for the purpose of calculating the relative importance values of the numbers. Consequently, the subsequent steps of this study entailed the determination of the relative priority values of the fuzzy synthetic values. This was achieved by employing the total integral method, which was developed by Liou and Wang [30]. with the assistance of Eq. (7). The value α denotes the optimism coefficient, which measures the degree of optimism exhibited by decision makers. The interval $\alpha = [0,1]$ is demonstrated in the following graph: As the degree of optimism of the relevant decision makers increases, the value of α approaches 1, and as it decreases, the value of α approaches 0.

$$I_T^{\alpha}(S_i) = \frac{1}{2}\alpha(m_i + u_i) + \frac{1}{2}(1 - \alpha)(l_i + m_i) = \frac{1}{2}[\alpha u_i + m_i + (1 - \alpha)l_i] \tag{7}$$

The third step of the process involves the calculation of the normalized weight vector of the fuzzy comparison matrix A, $W = (w_1, w_2, \dots \dots w_3)^T$. The calculation of T is outlined in Eq. (8). The weights obtained are synthesized hierarchically to obtain the final alternative weights. The weight vector W calculated here is not a fuzzy number.

$$W_x = \frac{I_T^{\alpha}(S_x)}{\sum_{k=1}^{n} I_T^{\alpha}(S_k)} \qquad x = 1, \dots, n \tag{8}$$

The fourth step of the process involves the calculation of the consistency ratio (CR). The purpose of this calculation is to verify the validity of the solutions developed by fuzzy AHP. In order to calculate the CR values in the fuzzy AHP method, firstly the fuzzy decision matrix values must be clarified by means of Eq. (9).

$$P(\widetilde{M}) = M = \frac{l+4m+u}{6} \tag{9}$$

Subsequent to the clarification of all values in the decision matrix, the steps of the classical AHP method were followed in order to calculate the CR value.

Accordingly, the value of λ_{maks} is calculated by using Eq. (10). Similarly, CI is calculated by using Eq. (10), and CR is calculated by using Eq. (11). The values reported in Table 2 [31] were utilized to determine the randomness index values (RI).

$$CI = \frac{(\lambda_{maks} - n)}{(n-1)} \tag{10}$$

$$CR = {CI}/{RI} \tag{11}$$

Table 2
Improved randomness index (RI) values for different matrix sizes

n	1	2	3	4	5	6	7	8	9
R.I.	0	0	0,58	0,90	1,12	1,24	1,32	1,41	1,45

The acceptance of the suitability of the decision matrices was determined by the CR values being less than 0.10 [31,24, 26].

As evidenced by the examples provided, the fuzzy AHP method has demonstrated efficacy in decision-making processes across a wide range of disciplines.

4.2 Best – Worst Method

BWM is a multi-criteria decision-making method that utilizes a comparison-based approach. This method involves the evaluation of the optimal criterion against other criteria, and subsequently, the evaluation of all criteria against the least optimal criterion. In the context of the BWM model, decision makers are not required to engage in exhaustive comparisons between all the criteria. The objective is to identify the most and least desirable criterion, and then to make pairwise comparisons between the best/worst criterion and the other criteria. A maximum mathematical model was constructed in order to ascertain the relative importances of the various criteria under consideration. In addition, a novel definition of consistency ratio was proposed with a view to ascertaining the reliability of the method.

However, in the context of BWM, ascertaining the optimal criterion becomes a challenging endeavor when the number of criteria is substantial. Therefore, it is necessary to apply a special procedure to determine the most suitable or least suitable criterion.

The following text is intended to provide a comprehensive overview of the subject matter. However, the BWM does offer some inspiration and enlightenment in two aspects. Firstly, it is evident that with the assistance of diagrams, tables and other linear tools, the diagram method can be widely used in thinking and analysis. Secondly, it is apparent that decision makers must first identify the best and worst criteria, and then make pairwise comparisons between each of these two criteria and other criteria [32, 33].

The first step in this process is to establish a set of decision criteria. In this step of the process, the decision maker determines the n criteria $(C_1, C_2, \dots, C_n)$ that will be used in the decision-making process.

The second step in the process is to identify the most and least desirable, as well as the most and least important, criteria.

The third step in the process is to determine the preference ratio of the best-selected criterion over all other criteria. This is achieved by assigning a number between 1 and 9 to the criterion. The relative importance of the criteria is determined by assigning a number between 1 and 9 to each criterion, with 1 representing an equal importance, 3 moderately higher importance, 5 highly important, 7 much more important, and 9 an extremely more important importance. Consequently, a vector known as Best-Others (A_B) is attained, which traverses from the optimal solution to the sub-optimal ones. The vector should be formulated as follows Eq. (12):

$$A_B = (\alpha_{B1}, \alpha_{B2}, \dots \dots \dots \alpha_{Bn}) \tag{12}$$

It is evident that each α_{Bj} in the vector A_B is indicative of the preference of the best criterion B over criterion j. Furthermore, it can be deduced that $\alpha_{BB} = 1$. This indicates that the most significant criterion will be evaluated in relation to itself.

The fourth step of the process is to determine the preference ratio of all other criteria with respect to the worst preferred criterion. This is to be achieved by using a number between 1 and 9. In this step, the relative importance of the other criteria over the worst criterion is determined by the decision maker using a number from 1 to 9. It is to be noted that, consequent to this step, the vector that is the worst of the others should be as follows Eq. (13):

$$A_W = \left(\alpha_{1W}, \alpha_{2W}, \dots \dots \dots \alpha_{n}{}_{W}\right)^T \tag{13}$$

In this vector, each a_{jw} indicates the preference of criterion j over the worst criterion W, and $a_{Ww} = 1$. This indicates that the most unfavorable criterion will be evaluated against itself.

In the final step of the process, it is necessary to determine the most appropriate weight for each criterion $(w_1, w_2, etc.)$. In this step, the objective is to ascertain the optimal weights of the criteria so as to provide maximum absolute differences. The optimal weight for the criteria is thus established as $W_B/W_j = a_{Bj}$ and $W_j/W_w = a_{jw}$ for each respective pair of W_B/W_j and W_j/W_w. The objective is to minimize the maximum absolute differences between the following:

$\left\{\left|w_B - a_{Bj}w_j\right|, \left|w_j - a_{jw}w_w\right|\right\}$ The objective is to identify a j value that can be incorporated into the following minimum-maximum model objective function as in Eq. (14), constraints as in Eq (15) and Eq. (16):

$$min\ \underset{j}{max}\left\{\left|w_B - a_{Bj}w_j\right|, \left|w_j - a_{jw}w_w\right|\right\} \text{ under constraints} \tag{14}$$

$$\textstyle\sum_j w_j = 1 \tag{15}$$

$$w_j \ \geq 0 \text{ for all } j\text{'s} \tag{16}$$

The problem equation is transformed into the following Eq. (17)-(21) linear programming problem:

$$min\xi^L \tag{17}$$

$$\left|\frac{w_B}{w_j} - \ a_{Bj}\right| \ \leq \ \xi, \text{ for all } j\text{'s} \tag{18}$$

$$\left|\frac{w_j}{w_w} - \ a_{jw}\right| \ \leq \ \xi, \text{ for all } j\text{'s} \tag{19}$$

$$\sum_j w_j = 1 \tag{20}$$

$$w_j \ \geq 0, \text{ for all } j\text{'s} \tag{21}$$

The completion and resolution of this model results in the determination of the optimal weights $(w_1, w_2, \ldots \ldots \ w_n)$ and the associated value. The value thus obtained is indicative of the consistency rates of the analyses. As the value increases, it is deduced that the comparisons become less reliable and their consistency is weak. Conversely, as the value decreases, it is concluded that the consistency ratios are high.

In the study, the summary application of the BWM is shown in Fig. 2.

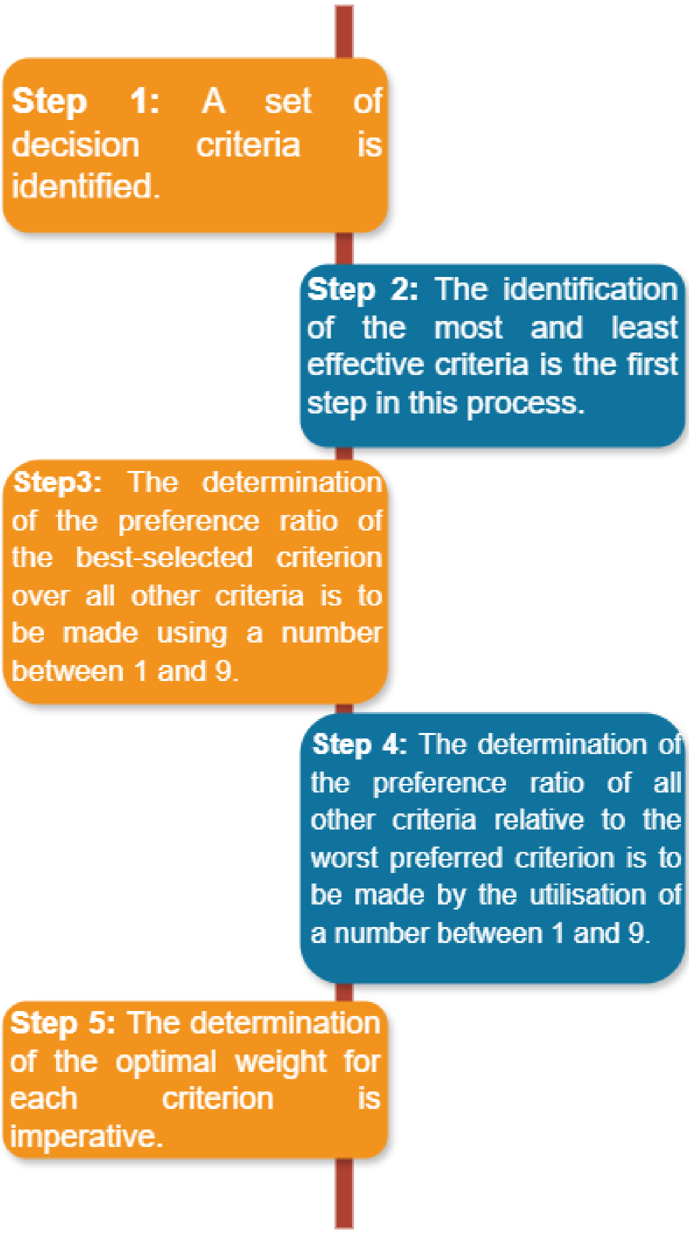

Fig. 2. Summary application steps of the Best-Worst Method.

5. Case Study

Within the scope of weighting the criteria to be used in the evaluation of the USV's to be selected for port security, a survey was conducted with 5 decision makers operating in the sector in order to obtain the comparison matrix to be used for AHP. While creating the pairwise comparison matrix, the scale reported in Table 3 [34] and frequently used in the literature was used. The same table also includes the triangular fuzzy number and linguistic variable expressions used in the Fuzzy AHP method.

Table 3
Scale of AHP and triangular fuzzy number (TFN)

AHP Scale	Linguistic variable	TFN Scale
1	Equal Importance	(1, 1, 1)
2	Between Equal and Moderate	(1, 2, 3)
3	Moderate Importance	(2, 3, 4)
4	Between Moderate and Strong	(3, 4, 5)
5	Strong Importance	(4, 5, 6)
6	Between Strong and Very Strong	(5, 6, 7)
7	Very Strong Importance	(6, 7, 8)
8	Between Very Strong and Extreme	(7, 8, 9)
9	Extreme Importance	(9, 9, 9)

As a result of these surveys, consistency analysis was performed for each evaluation of 5 decision makers. Then, before proceeding to the fuzzy method calculations, the evaluations of the 5 decision makers were geometrically averaged to form a single matrix. The matrix displaying the individual evaluations of the decision makers, consolidated into a single matrix through the utilization of geometric means, is reported in Table 4.

Table 4
Aggregated evaluation values.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	1	2	4	4	1	1	2	4	5
C_2	0,5	1	2	4	1	1	2	2	3
C_3	0,25	0,5	1	2	1	1	1	2	3
C_4	0,25	0,25	0,5	1	1	1	1	2	2
C_5	1	1	1	1	1	2	3	4	5
C_6	1	1	1	1	0,5	1	2	2	3
C_7	0,5	0,5	1	1	0,333333	0,5	1	3	3
C_8	0,25	0,5	0,5	0,5	0,25	0,5	0,333333	1	2
C_9	0,2	0,333333	0,333333	0,5	0,2	0,333333	0,333333	0,5	1

Subsequently, the weights of the criteria were obtained by applying the operations of the Chang's Extent Method to this matrix, respectively. The matrix containing the fuzzy numbers prior to the initiation of the Chang's Extent Method operations is given in Table 5, while the matrix illustrating the criteria weights obtained as a consequence of the operations is reported in Table 6.

Table 5
Fuzzy numbers prior to the Chang's extent method

	C1			C2			C3			C4			C5			C6			C7			C8			C9		
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
C1	1,00	1,00	1,00	1,00	2,00	3,00	3,00	4,00	5,00	3,00	4,00	5,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	2,00	3,00	3,00	4,00	5,00	4,00	5,00	6,00
C2	0,33	0,50	1,00	1,00	1,00	1,00	1,00	2,00	3,00	3,00	4,00	5,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	2,00	3,00	1,00	2,00	3,00	2,00	3,00	4,00
C3	0,20	0,25	0,33	0,33	0,50	1,00	1,00	1,00	1,00	1,00	2,00	3,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	2,00	3,00	2,00	3,00	4,00
C4	0,20	0,25	0,33	0,20	0,25	0,33	0,33	0,50	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	2,00	3,00	1,00	2,00	3,00
C5	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	2,00	3,00	2,00	3,00	4,00	3,00	4,00	5,00	4,00	5,00	6,00
C6	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,33	0,50	1,00	1,00	1,00	1,00	1,00	2,00	3,00	1,00	2,00	3,00	2,00	3,00	4,00
C7	0,33	0,50	1,00	0,33	0,50	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,25	0,33	0,50	0,33	0,50	1,00	1,00	1,00	1,00	2,00	3,00	4,00	2,00	3,00	4,00
C8	0,20	0,25	0,33	0,33	0,50	1,00	0,33	0,50	1,00	0,33	0,50	1,00	0,20	0,25	0,33	0,33	0,50	1,00	0,25	0,33	0,50	1,00	1,00	1,00	1,00	2,00	3,00
C9	0,17	0,20	0,25	0,25	0,33	0,50	0,25	0,33	0,50	0,33	0,50	1,00	0,17	0,20	0,25	0,25	0,33	0,50	0,25	0,33	0,50	0,33	0,50	1,00	1,00	1,00	1,00

Table *6*

Criteria weights with Chang's extent method

Criterias	Weights
C_1	0,192854
C_2	0,192854
C_3	0,130074
C_4	0,035908
C_5	0,192854
C_6	0,146866
C_7	0,108591
C_8	0
C_9	0

An examination of the criteria weights obtained following the Fuzzy AHP process reveals the order to be C_1=C_2=C_5>C_6>C_3>C_7>C_4>C_8=C_9This ranking indicates that criteria 1, 2 and 5 are of paramount importance, with their respective weights being of equal significance. Conversely, criteria C_8 and C_9 are of least importance. The criterion weight values of $C_8$and C_9 are both set to 0, indicating that these criteria are of negligible importance to decision makers. Although the criterion weight of 0 is a common occurrence in fuzzy AHP, it is possible to interpret this as a methodological limitation. In Figure 3, the results of criteria weights with Fuzzy AHP are given as a bar chart.

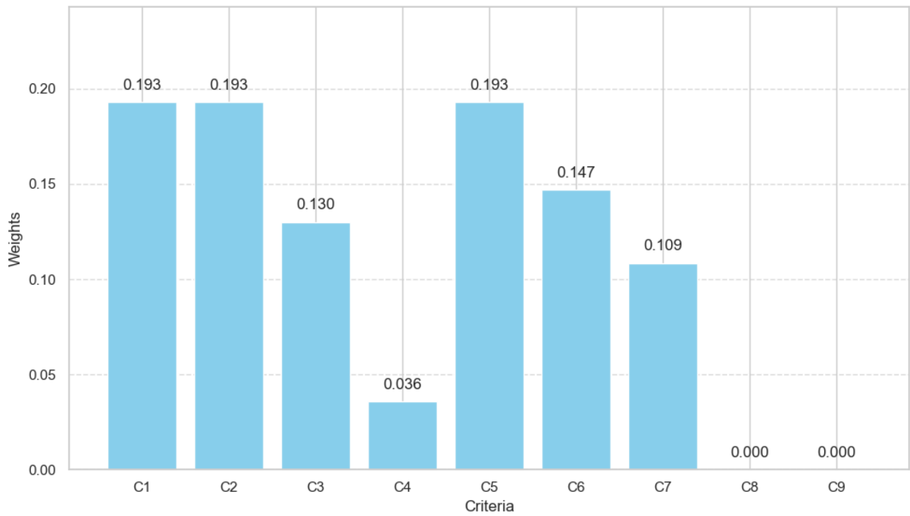

Fig. 3. Result of criteria weights with fuzzy AHP

To compare the weights obtained with the fuzzy AHP, weights were obtained for the same criteria using the BWM. Within the BWM, the same five decision-makers made their evaluations, and these evaluations were processed as a single evaluation by taking the geometric mean.

A consistency analysis was performed for the evaluations made with this method, and the steps of the method were then applied. Data from the best table, whose geometric means were calculated and combined into a single evaluation, are given in Table 7, and data from the worst table are reported in Table 8.

Table 7
Best Score Table

Best to Others	Endurance
Endurance	1
Range	2
Operational Speed	4
Payload Capacity	4
Sensors System	2
Data Security	3
Navigation System	3
Maintenance Cost	6
Investment Cost	7

Table 8
Worst Score Table

Others to the Worst	Data Security
Endurance	6
Range	6
Operational Speed	4
Payload Capacity	3
Sensors System	6
Data Security	4
Navigation System	4
Maintenance Cost	2
Investment Cost	1

The weights obtained when we solved the formulas specified in the method detailing section with the Excel Solver add-in are reported in Table 9.

Table 9
Criteria Weights with Best Worst Method

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Weights	0,252	0,153	0,077	0,077	0,153	0,102	0,102	0,051	0,033

When the criteria weights obtained after the application of the BWM are examined, it is seen that the ranking C_1>C_2=C_5>C_6=C_7>C_3=C_4>C_8=C_9 is obtained. This ranking shows that criterion 1 is the most important criterion, while C_8 and C_9 are the worst criteria with equal importance. Regarding the other criteria, C_2 and C_5, $C_6$and C_7, and C_3 and $C_4$are of equal importance. In Figure 4, the results of criteria weights with Best Worst are given as a bar chart.

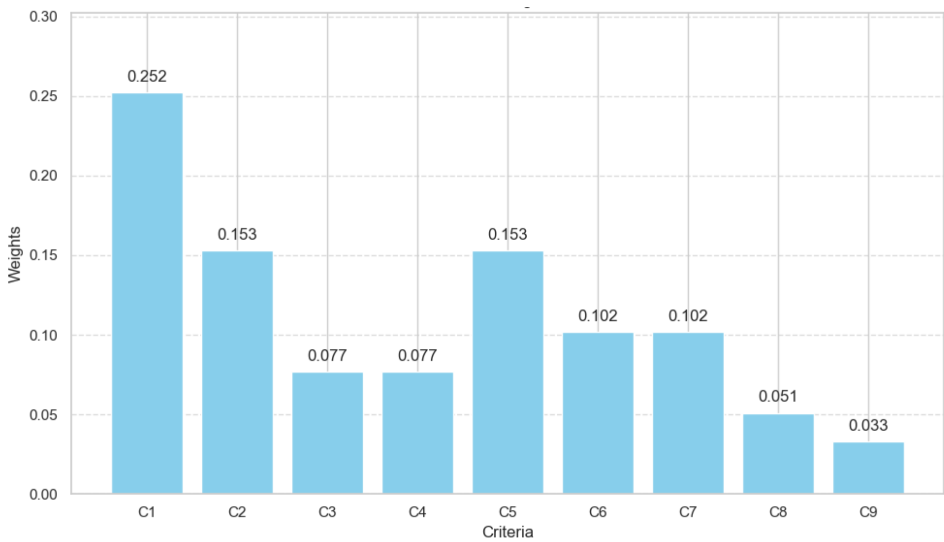

Fig. 4. Result of criteria weights with Best Worst

6.Discussion and Conclusion

In the contemporary era, technological advancements have emerged as the primary catalyst for transformation within the defense industry. In particular, unmanned and autonomous systems have gained significant importance due to their ability to mitigate the risk of human involvement in military operations and enhance operational effectiveness. UUVs, an integral component of this transformation, are utilized in numerous critical missions, including reconnaissance, surveillance, mine countermeasures, underwater mapping and logistic support. The capacity of these systems to substitute for manned assets, particularly in waters deemed to be at risk of conflict, serves to augment their strategic value.

In this study, the reconnaissance, surveillance and protection function – which is one of the functions of UUVs – is evaluated in the context of port security. A comprehensive evaluation was conducted in order to determine the most effective methods for ensuring port security. This evaluation involved a thorough review of the existing literature and consultation with experts in the field. The evaluation sought to identify the most crucial criteria for ensuring port security, employing a variety of methods to achieve this objective.

The determination of criteria weights was achieved by employing fuzzy AHP and BWM methodologies. It is understood that the result obtained after the implementation of Fuzzy AHP and the result obtained after the application of BWM are similar to each other. While C_1 and C_2 are the most significant criteria in Fuzzy AHP, C_1 is the most significant criterion in Best Worst Method. Conversely, criteria C_8 and C_9 emerge as the least effective criteria, exhibiting equivalent weights in both methodologies. The observation that analogous results are obtained in both applications lends support to the validity of the findings.

The findings of this study demonstrate that when utilizing UUVs for port security purposes, the paramount criterion is "Endurance", while "Maintenance Cost" and "Investment Cost" emerge as the least significant. Consequently, administrations aspiring to guarantee security with UUVs in ports must give due consideration to the "Endurance" criterion in the selection of UUVs. Furthermore, it is imperative to note that the criteria of "Maintenance Cost" and "Investment Cost" should not be taken into consideration during the selection process of UUVs. These findings can be of use to administrations seeking to enhance the effectiveness and efficiency of port security measures.

In future studies on the use of UUVs in port security, various alternatives can be selected and alternative rankings can be made among the determined criteria. In addition, the efficacy of q-ROF fuzzy sets in reducing uncertainty has been demonstrated.

Author Contributions

Conceptualization, A.T., Ş.D., B.G., O.G. and S.B.; methodology, A.T., O.G. and M.K.B.; analysis, A.T., Ş.D. and O.G.; writing—original draft preparation, A.T., Ş.D., B.G. and O.G.; writing—review and editing, AT, Ş.D., B.G., O.G. and S.B. All authors have read and agreed to the published version of the manuscript." Authorship must be limited to those who have contributed substantially to the work reported.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Stein, M. (2018). Integrating unmanned vehicles in port security operations: an introductory analysis and first applicable frameworks. *Oceans Yearbook*, *32*, 556-583. https://doi.org/10.1163/22116001-03201022.

[2] Craven, P. J., Sutton, R., & Burns, R. S. (1998). Control strategies for unmanned underwater vehicles. The Journal of Navigation, 51(1), 79-105. https://doi.org/10.1017/S0373463397007601.

[3] Kou, L., Xiang, J., Li, Y., & Bian, J. (2018). Stability and nonlinear controllability analysis of a quadrotor-like autonomous underwater vehicle considering variety of cases. International Journal of Advanced Robotic Systems, 15(6), https://doi.org/10.1177/1729881418819401.

[4] Yan, R. J., Pang, S., Sun, H. B., & Pang, Y. J. (2010). Development and missions of unmanned surface vehicle. Journal of Marine Science and Application, 9, 451-457. https://doi.org/10.1007/s11804-010-1033-2

[5] Corfield SJ, Young JM (2006). Unmanned surface vehicles–game changing technology for naval operations, Ch.15 in Advances in Unmanned Marine Vehicles. Institution of Electrical Engineers, 311-328. DOI:10.1049/PBCE069E_ch15.

[6] Boretti, A. (2024). Unmanned surface vehicles for naval warfare and maritime security. The Journal of Defense Modeling and Simulation, https://doi.org/10.1177/15485129241283056.

[7] Ghazali, M. H. M., Satar, M. H. A., & Rahiman, W. (2024). Unmanned surface vehicles: From a hull design perspective. Ocean Engineering, 312, 118977. https://doi.org/10.1016/j.oceaneng.2024.118977.

[8] Odu, G. O. (2019). Weighting methods for multi-criteria decision making technique. *Journal of Applied Sciences and Environmental Management*, *23*(8), 1449-1457. https://doi.org/10.4314/jasem.v23i8.7.

[9] Ozcalici, M. (2022). Allocation with multi criteria decision making techniques. Decision Making: Applications in Management and Engineering, 5(2), 78-119. https://doi.org/10.31181/dmame0305102022o.

[10] Zavadskas, E. K., & Podvezko, V. (2016). Integrated determination of objective criteria weights in MCDM. International Journal of Information Technology & Decision Making, 15(02), 267-283. https://doi.org/10.1142/S0219622016500036.

[11] Gürler, H. E., Özçalıcı, M., & Pamucar, D. (2024). Determining criteria weights with genetic algorithms for multi-criteria decision making methods: The case of logistics performance index rankings of European Union countries. Socio-Economic Planning Sciences, 91, 101758. https://doi.org/10.1016/j.seps.2023.101758.

[12] Keshavarz-Ghorabaee, M., Amiri, M., Zavadskas, E. K., Turskis, Z., & Antucheviciene, J. (2021). Determination of objective weights using a new method based on the removal effects of criteria (MEREC). Symmetry, 13(4), 525. https://doi.org/10.3390/sym13040525.
[13] Ginevičius, R. (2011). A new determining method for the criteria weights in multicriteria evaluation. International Journal of information technology & decision making, 10(06), 1067-1095. https://doi.org/10.1142/S0219622011004713.
[14] Žižović, M., & Pamucar, D. (2019). New model for determining criteria weights: Level Based Weight Assessment (LBWA) model. Decision making: applications in management and engineering, 2(2), 126-137. https://doi.org/10.31181/dmame1902102z.
[15] Kobryń, A. (2017). DEMATEL as a weighting method in multi-criteria decision analysis. Multiple Criteria Decision Making, (12), 153-167. DOI: 10.22367/mcdm.2017.12.11.
[16] Stanujkic, D., Zavadskas, E. K., Karabasevic, D., Smarandache, F., & Turskis, Z. (2017). The use of the pivot pairwise relative criteria importance assessment method for determining the weights of criteria. Infinite Study.
[17] Kolios, A., Mytilinou, V., Lozano-Minguez, E., & Salonitis, K. (2016). A comparative study of multiple-criteria decision-making methods under stochastic inputs. Energies, 9(7), 566. https://doi.org/10.3390/en9070566.
[18] Altundaş, A., Kurtay, K. G., & Erol, S. (2022). Sınır güvenliği ve müdahale görevi yapan İHA'ların ÇKKV yöntemleri ile değerlendirilmesi. Savunma Bilimleri Dergisi, (42), 155-185. https://doi.org/10.17134/khosbd.1049863.
[19] Hozairi, H., Buhari, B., Lumaksono, H., & Tukan, M. (2019). Selection of Marine Security Policy using Fuzzy-AHP TOPSIS Hybrid Approach. Knowl. Eng. Data Sci., 2(1), 19-30.
[20] Nichols, C. R., Xiros, N. I., & Pavy, J. (2016). Maritime Advanced Geospatial Intelligence Craft for Oil Spill Response: Selected Resources and Annotations.
[21] Xin, J., Li, S., Sheng, J., Zhang, Y., & Cui, Y. (2019). Application of improved particle swarm optimization for navigation of unmanned surface vehicles. Sensors, 19(14), 3096. https://doi.org/10.3390/s19143096.
[22] Abdullah, A. G., Shafii, M. A., Pramuditya, S., Setiadipura, T., & Anzhar, K. (2023). Multi-criteria decision making for nuclear power plant selection using fuzzy AHP: Evidence from Indonesia. Energy and AI, 14, 100263. https://doi.org/10.1016/j.egyai.2023.100263.
[23] Guliyev, J., Güneri, B., Konur, M., Duymaz, Ş., & Türk, A. (2025). Offshore wind power site selection in Türkiye using q-rung orthopair fuzzy sets and the COPRAS method. Journal of Operations Intelligence, 3(1), 278-302. https://doi.org/10.31181/jopi31202551.
[24] Kabir, G., & Sumi, R. S. 2014. "Power substation location selection using fuzzy analytic hierarchy process and PROMETHEE: A case study from Bangladesh." Energy, 72, 717-730. https://doi.org/10.1016/j.energy.2014.05.098.
[25] Srichetta, P., and Thurachon, W., 2012. "Applying fuzzy analytic hierarchy process to evaluate and select product of notebook computers." International Journal of Modeling and Optimization, vol.2, no.2, pp.168. https://doi.org/10.7763/IJMO.2012.V2.105.
[26] Şen, C. G., & Çınar, G. 2010. "Evaluation and pre-allocation of operators with multiple skills: A combined fuzzy AHP and max–min approach." Expert Systems with Applications, 37(3), 2043-2053. https://doi.org/10.1016/j.eswa.2009.06.075.
[27] Chang, D. Y. 1996. "Applications of the extent analysis method on fuzzy AHP." European journal of operational research, 95(3), 649-655. https://doi.org/10.1016/0377-2217(95)00300-2.
[28] Göksu, A., & Güngör, İ. 2008. "Fuzzy Analytic Hierarchical Process and Its Application in University Preference Ranking." Süleyman Demirel University Journal of Faculty of Economics and Administrative Sciences, 13(3), 1-26.
[29] Wang, Y. M., Luo, Y., & Hua, Z. 2008. "On the extent analysis method for fuzzy AHP and its applications." European journal of operational research, 186(2), 735-747. https://doi.org/10.1016/j.ejor.2007.01.050.
[30] Liou, T. S., & Wang, M. J. J. 1992. "Ranking fuzzy numbers with integral value." Fuzzy sets and systems, 50(3), 247-255. https://doi.org/10.1016/0165-0114(92)90223-Q.
[31] Saaty TL. Group Decision Making and the AHP. Anal. hierarchy Process 1989: 59–67. https://doi.org/10.1007/978-3-642-50244-6_4
[32] Rezaei, J., Wang, J. & Tavasszy, L. (2015). "Linking Supplier Development to Supplier Segmentation Using Best–Worst Method". Expert Systems with Applications, 42, 9152-9164. https://doi.org/10.1016/j.eswa.2015.07.073.
[33] Mou, Q., Xu, Z. & Liao, H. (2016). "An Intuitionistic Fuzzy Multiplicative Best-Worst Method for Multi-Criteria Group Decision Making". Information Sciences, 374, 224–239. https://doi.org/10.1016/j.ins.2016.08.074.
[34] Deng H. Multicriteria analysis with fuzzy pairwise comparison. IEEE Int Conf Fuzzy Syst 1999;2(x):726–31. https://doi.org/10.1109/fuzzy.1999.793038.