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Understanding the core determinants of bunker supply vessel selection for maritime industry: an integrated fuzzy-AHP and fuzzy-TOPSIS approach

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Abstract

Purpose – Selecting optimal bunker supply vessels (BSVs) is critical for shipping companies to enhance operational efficiency, control costs and meet environmental goals. This study identifies the core determinants of BSV selection to support informed decision-making in maritime logistics.

Design/methodology/approach – An integrated fuzzy analytical hierarchy process (fuzzy-AHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (fuzzy-TOPSIS) approach is employed. About eight industry experts evaluated ten BSV alternatives based on 20 sub-criteria spanning economic, operational, environmental and technological dimensions, including fuel cost, bunker consumption, ship age, bunker capacity and technological equipment level.

Findings – Economic and operational criteria dominate BSV selection, with fuel cost (0.089 weight) and bunker consumption (0.077 weight) being the most influential. Vessels A6 and A2 ranked highest due to their fuel efficiency, large bunker capacity, fast discharge rates, low carbon footprint and advanced technology. The framework demonstrates significant impacts on operational and environmental performance.

Originality/value – Unlike prior studies focusing on bunker purchasing or port selection, this research uniquely integrates economic, operational, environmental and technological criteria using a hybrid fuzzy-AHP and fuzzy-TOPSIS approach. It addresses uncertainties in BSV selection, offering a novel decision-support framework for sustainable maritime logistics.

Keywords Maritime, Bunker supply vessel (BSV), Fuzzy-AHP, Fuzzy-TOPSIS

Paper type Research article

1. Introduction

The maritime industry is highly energy-intensive, attributed to the high volume of the cargoes transported and long-distance transportation. Bunkering represents the most significant energy supply for most conventional ships engaged in maritime transportation. Bunker costs ranging from 50 to 60% account for a substantial share of total operational costs (Mazraati, 2011). This share is directly related to the competitiveness of maritime companies. Because the bunker supply process directly impacts operational, financial and environmental efficiency. In practice, bunker supplies are divided into two main methods: ship-to-ship or truck-to-ship operations, which are common, especially in long port stays. The sole method is typically a ship-to-ship operation at anchorage, traverse, drifting or short port stays. The features of a bunker vessel are at the centre of a bunkering decision process. The process is crucial as it influences financial, technical, operational and environmental performance. Therefore, individual characteristics of bunker supply vessels involved in a bunkering operation are considered. Consequently, the selection of bunker supply vessels poses a pivotal decision problem for shipping companies seeking to optimize their operations, protect the environment and maintain cost control. It is of paramount importance that the appropriate

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type and quantity of fuel be supplied on time to guarantee the optimal functioning of merchant vessels.

Bunker supply vessels (BSVs), which are the vessels that play the most crucial role in the provision of ship fuels, are specifically constructed to facilitate the supply of fuel to ships operating in ports and at sea. In addition, effective bunker supply operations help enhance the sustainability of seaborne trade. Selecting these ships is a very important decision-making process with operational and strategic implications. Using an unsuitable vessel can result in the collapse of the supply chain, reduced operational efficiency and higher costs. According to the International Chamber of Shipping (ICS, 2023), the International Maritime Organization (IMO) recorded 4,800 BSVs worldwide in 2023, with different capacities and capabilities, including support for alternative fuels like LNG. Since quantity, capacity and capabilities are heterogeneous, decision-making becomes more complicated. The purpose of this study is to identify significant factors for BSV selection and develop a decision-support framework incorporating an integrated fuzzy analytical hierarchy process (fuzzy-AHP) and fuzzy Technique for Order Preference by Similarity to Ideal Solution (fuzzy-TOPSIS) model using economic, operational, technological and environmental considerations to improve bunkering performance.

Maritime bunker operations have recently become a topic of interest in the literature, driven by critical concerns about environmental and economic aspects. Several studies support decisions related to maritime bunkering operations from various perspectives. The contracts and purchasing strategies employed in the bunker supply process influence vessel selection (Plum *et al*., 2014). Additionally, vessel speed optimization in the context of liner shipping operations and bunker port selection are important considerations within the broader framework of bunker supply vessel selection (Sheng *et al*., 2014). However, research integrating economic, operational, environmental and technological criteria for optimal BSV selection using advanced multi-criteria decision-making (MCDM) methods is scarce. Existing studies often focus on related aspects, such as bunker purchasing or port selection, but rarely address the comprehensive evaluation of BSV characteristics. This study fills this gap by employing a hybrid fuzzy-AHP and fuzzy-TOPSIS approach to handle uncertainties and provide a robust framework for BSV selection, offering novel insights for sustainable maritime logistics.

The study is structured into six sections. The next section analyses the methods and existing research used in BSV selection through a literature review, thereby identifying knowledge gaps and research needs in this field. Section 3 explains the adopted methods. Section 4 presents the findings, Section 5 discusses results and limitations, and Section 6 concludes with implications and future directions.

2. Literature review

2.1 Bunker supply vessels (BSVs)

The presence of 4,800 BSVs worldwide reflects the substantial demand for bunker supply in the maritime transport sector. This would mean that competition within the business is also significant, with companies striving to make such vessels more efficient. An ordinary BSV has the characteristics specified in Table 1 according to the International Chamber of Shipping:

The versatility of BSVs, ranging between 1,000 and 5,000 tonnes, enhances their applicability in refuelling diverse ships. This is particularly pertinent in meeting the bunker requirements of large ships. The excellent manoeuvrability of BSVs allows them to navigate easily along busy harbour channels, facilitating efficient and effective bunkering operations that improve overall operating efficiency. The ability to work with various bunker fuel types plays a critical role in maintaining compliance with environmental regulations in shipping. The use of alternative fuels, such as liquefied natural gas and ultra-low sulphur fuel oil, ensures minimal environmental impact. Furthermore, the 10–15 knots vessel speed range allows efficient quick provisioning of fuel to BSVs, thereby minimizing waiting time for refuelling.

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Table 1. BSV number (ICS, 2023)

Specification	Value
Total number of vessels	4,800
Average transport capacity (tonnes)	1,000–5,000
Fuel storage capacity (tonnes)	500–2,500
Manoeuvrability	High
Operating speed (knots)	10–15
Fuel types	IFO, MDO, LNG, ULSFO
Length (metres)	30–100
Width (metres)	8–20
Draft (metres)	3–6
Main engine power (HP)	1,000–3,500
Certification	ISM, ISPS, MARPOL

Source(s): Author's own elaboration based on the BSVs methodology and report of the International Chamber of Shipping (2023)

This process optimization translates into cost savings. These aspects – capacity, manoeuvrability, fuel type and speed – are significant factors in BSV selection, influencing cost, efficiency and compliance (Aymelek *et al*., 2014).

The choice of BSVs is a multifaceted process requiring consideration of numerous factors. These include ship cargo capacity, manoeuvrability, bunker storage space, operations efficiency and safety features. Also considered are the compatibility of the bunker with the quality requirements, procurement time and operational flexibility while making the choice. Greater use of alternative fuels such as LNG is transforming BSV design and fuel selection norms (Aymelerk *et al*., 2014).

2.2 Maritime bunker operations

Maritime bunker operations have recently become a topic of interest in the literature, driven by critical concerns about environmental and economic aspects. Several studies support decisions related to maritime bunkering operations from various aspects. Research on the supply process of ship bunkers and their economic impacts on shipping firms began in the late 1990s. These early studies explored the influence of fluctuating bunker prices and port-based bunker supply processes on the profitability of shipping firms (Berg-Andreassen, 1997). The efficiency of fuel supply processes significantly impacts the timely and cost-effective execution of ship operations. Additionally, the variability in bunker prices directly influences the strategic fuelling policies of shipping companies (Stopford, 1997). Ha *et al*. (2023) used a fuzzy analytic hierarchy process to identify key factors in LNG bunkering port selection, emphasizing strategic location, accessibility and infrastructure. Recent studies, such as Arıcan and Kara (2024) and Wang *et al.* (2011), applied MCDM methods to optimize ship selection and bunkering, focusing on operational and economic criteria. Yang and Lam (2023) assessed the operational and economic feasibility of using ammonia as a marine fuel, specifically focusing on the bunkering supply chain. The study identified key factors, including the BSV selection, including the number and capacity, bunkering flow rate and demand. The findings indicate that the number of ammonia bunker supply vessels is the most sensitive parameter, with a potential impact of up to 15.2% on annual operational costs. Fuentes *et al*. (2024) examined the impact of waiting times at bunkering ports on the decision-making of tramp ship operators. However, the studies particularly focusing on optimum bunker vessel selection are limited. Miranda *et al*. (2024) developed a Bunkering Reliability Index to assess the reliability of truck-to-ship bunkering operations. On the other hand, Choi *et al*. (2025) used a fuzzy analytic hierarchy process to assess the relative importance of different risk factors in ship-to-ship LNG bunkering, providing a structured approach to risk management. The study identified and

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categorized various risks into four main groups: operational risks, human error, external environmental factors and equipment failure. The study identifies the occurrence of operational risks and human errors as key causative factors that are likely to contribute to possible accidents. They are giving insights regarding the improvement in safety protocols and training schemes within the industry. Specifically, breakdowns in equipment, like issues with hoses, pumps and the tanks themselves can be able to elucidate possible breakdowns in bunkering operations. Since equipment failures in vessels may have adverse health and environmental consequences, it is important to understand the determinants and have a decision support system. Tavana *et al*. (2018) conducted a study on the subject and proposed a decision support system to maximize bunker fuel usage in shipping activities. The study demonstrated that the decision support system resulted in a significant reduction in ship bunker consumption costs and bunker fuel buying processes and also explored ways of improving vessel speed and minimizing bunker consumption.

In recent years, environmental regulations imposed by the International Maritime Organization have changed processes of fuel supply. The sulphur limitation placed by the IMO during the year 2020 has forced a massive shift in ships' bunker fuel preferences (IMO, 2020). These regulations, combined with the IMO objective of limiting carbon emissions by 40% between 2023 and 2030 (IMO, 2018), have brought about a transition towards cleaner fuels such as LNG, which produces 20–30% less (Aymelek *et al*., 2014). Emerging fuels like ammonia and hydrogen are also shaping BSV design with stricter environmental regulations (Yang and Lam, 2023). These changes require BSVs to adjust their storage and operational capacity. According to Plum *et al*. (2014), as quoted, the enforcement of environmental policies has increased the pressure on bunker prices, which is a challenge to shipping companies in terms of cost control. Similarly, Sheng *et al*. (2014) examined the impact of speed optimization and bunker supply port selection on bunker consumption and environmental impacts in liner shipping. The shipping sector contributed approximately 1.9 bn tonnes of CO_2 in 2020, leading to the implementation of global regulations to reduce the carbon emissions in the sector (IMO, 2020). The International Maritime Organization has also set a target to reduce the carbon emissions in the shipping sector by at least 40% from 2023 to 2030 (IMO, 2018). In accordance with these goals, alternative fuel consumption and energy efficiency are critical shipping parameters. For example, alternative fuel consumption, including liquefied natural gas, is one of the main measures for minimizing environmental traces. According to Aymelek *et al*. (2014), LNG has been reported to reduce carbon emissions by 20–30%. Recent years' price volatility of bunkers and international organizations developing strict environmental regulations have compelled shipping lines to implement more efficient bunker supply chains. Similarly, implementation of new IMO regulations to reduce carbon emissions in shipping has compelled bunker supply chains to go through a radical shift. Thus, environmental concerns must be integrated into BSV selection. In this context, environmental concerns must be considered when bunkering vessel selection is being carried out (Görçün and Küçükönder, 2021, p. 213). Optimization of bunker procurement processes has been found to yield cost savings and reduced environmental impact (Plum *et al*., 2014; Zhao *et al*., 2022). Multi-criteria decision-making techniques can be applied suitably to bunkers' management and procurement (Chen and Hwang, 1992; Yoon and Hwang, 1995). Wang *et al*. (2011) investigated the impact of bunker consumption by ships and the refuelling process and determined that fuel is a significant cost component in ship operation. Similarly, Aymelek *et al*. (2014) investigated the changes in fuel bunkering processes as a result of the use of alternative fuels, such as LNG.

2.3 BSV selection in shipping companies

BSV selection is a critical decision for shipping companies, impacting operational efficiency, cost management and regulatory compliance. Companies typically evaluate BSVs based on:

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(1) Fuel compatibility: Ensuring the BSV supports the ship's fuel type (e.g. LNG for LNG-powered vessels, ULSFO for low-sulphur compliance) (ICS, 2023).

(2) Bunker capacity and discharge rate: Larger capacities and faster discharge rates reduce bunkERING times, critical for busy ports like Singapore (Ha *et al*., 2023).

(3) Port logistics: BSVs must navigate port constraints and comply with local regulations, such as MARPOL standards.

(4) Environmental performance: Preference for BSVs with low carbon footprints aligns with IMO's 2020 sulphur cap and 2030 carbon reduction goals (IMO, 2020, 2018).

Selection processes vary by ship type and company. For example, container shipping firms prioritize high-capacity BSVs for frequent refuelling, while tanker operators may focus on BSVs handling heavy fuel oil or LNG (Yang and Lam, 2023). Collaboration between ship operators, chartering managers and port authorities ensures seamless bunkering. However, few studies provide a comprehensive framework integrating economic, operational, environmental and technological criteria for BSV selection, a gap this study addresses with a hybrid fuzzy-AHP and fuzzy-TOPSIS approach.

Table 2 organizes the literature on bunker and ship selection. BSV selection is vital for efficient bunkering and cost minimization in the maritime industry. While studies explore supply chain management, ship operations and environmental impacts using MCDM and optimization, few integrate economic, operational, environmental and technological factors for optimal BSV selection. This study addresses this gap by employing a hybrid fuzzy-AHP and fuzzy-TOPSIS approach, offering a robust decision-support framework for sustainable maritime logistics.

3. Material and methods

This study will analyse the selection of BSVs in the maritime sector using the fuzzy analytical hierarchy process (fuzzy AHP) and the Fuzzy TOPSIS methods. These two methods are effectively employed in multi-criteria decision-making processes due to their capacity to accommodate uncertainties and fuzzy data. The following section provides a step-by-step explanation of these two methods. In the context of these methods, a survey was conducted with eight experts working in bunker maritime companies. These managers, who participated in the survey, are considered experts in their respective fields. Table 3 illustrates the total number of bunker ships managed by these experts and the characteristics of the experts.

The experts were selected using purposive sampling, targeting professionals with at least 10 years of experience in BSV operations or chartering, ensuring deep industry knowledge. The sample size of eight is justified by similar studies in fuzzy-AHP/TOPSIS, such as Ha *et al.* (2023), which used 6–10 experts for comparable maritime analyses. To mitigate bias, responses were anonymized and a Delphi-like iterative feedback process was used to refine expert judgements.

The criteria weights for BSV selection may vary depending on ship type (e.g. LNG-powered vs low-sulphur fuel vessels) and company type (e.g. container vs tanker operators). For instance, LNG-compatible BSVs may prioritize environmental criteria like emission rates, while tankers may focus on bunker capacity. These variations are reflected in the data from Appendix A, guiding the hierarchical analysis.

In this context, the created BSV selection hierarchy diagram is given in Figure 1. The main criteria determined are economic, operational, environmental and technological. It includes five economic, five operational sub-criteria, five environmental sub-criteria and five technological sub-criteria. In this Figure, c_i shows the sub-criteria $(i = 1, 2, \ldots, n)$. The criteria and sub-criteria given in the figure will be shown with their abbreviations in the study hereafter.

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Table 2. Studies on bunker operations

Year	Author(s)	Title	Key subjects
2009	Besbes and Savin (2009)	When Promotions Meet Operations: Cross-Selling and Its Effect on Call Centre Performance	Bunker management, route selection
2011	Wang *et al.* (2011)	The Rationale Behind and Effects of Bunker Adjustment Factors	Bunker adjustment factors, shipping
2011	Mazraati (2011)	Challenges and Prospects of International Marine Bunkers' Demand	Bunker demand, shipping industry
2014	Aymelek *et al.* (2014)	LNG bunker	LNG, bunker management, energy efficiency
2014	Plum *et al.* (2014)	Bunker Purchasing with Contracts	Bunker purchasing, contract management
2015	Sener and Ozturk (2015)	Ship selection	Ship selection, quality function development (QFD)
2016	Emovon (2016)	Ship maintenance selection	Ship systems, maintenance strategies, multi-criteria decision-making
2019	De *et al.* (2019)	Bunker Management Strategies	Bunker management, sustainability
2019	De *et al.* (2019)	Bunkering Policies	Bunker management, liner shipping
2021	Dos Santos *et al.* (2021)	Warship selection strategies	Multi-criteria decision-making, warship selection
2022	Gavalas *et al.* (2022)	Shipping industry key performance indicators	Ship construction, performance indicators
2022	Zhao *et al.* (2022)	Bunker management and policies	Ship scheduling, bunker management
2022	Görçün (2022)	Second-hand tanker selection	Chemical tankers, multi-criteria decision making
2023	Ha *et al.* (2023)	LNG bunkering port selection	Interpretive structural modelling (ISM)
2023	Yang and Lam (2023)	Operational and economic evaluation of ammonia bunkering	A discrete event simulation model for bunker supply chain
2024	Fuentes *et al.* (2024)	Waiting times on the bunkering decision for tramp ships	Optimisation
2024	Arıcan and Kara (2024)	Chemical tanker selection for different cargo types	Chemical tankers, Fuzzy AHP, Fuzzy TOPSIS
2024	Miranda *et al.* (2024)	Reliability in LNG bunkering operations	Reliability model
2025	Choi *et al.* (2025)	Analysing risk factors in ship-to-ship liquefied natural gas bunkering operations	The consistent fuzzy preference relations method

Source(s): Author's own elaboration based on the BSVs methodology and literature review

The relative weights of BSV selection criteria are determined employing fuzzy AHP, while BSVs are ranked employing fuzzy TOPSIS. In recent years, fuzzy AHP and fuzzy TOPSIS have emerged as the two most preferred methods. They assist in overcoming the challenges associated with numerical comparisons in instances where the preferences of experts are uncertain (Radionovs and Uzhga-Rebrov, 2015, p. 165). In other words, they offer the benefit of attaining superior outcomes by combining traditional AHP/TOPSIS with fuzzy set theory (Arıcan and Kara, 2024, p. 12). Both methods employ linguistic variables for the evaluation of criteria and alternatives. Therefore, it is essential to define the appropriate linguistic variables and their corresponding fuzzy numbers. In this context, triangular fuzzy numbers (TFNs) are a popular choice due to their computational efficiency and simplicity. A triangular fuzzy number is defined by a triple (a, b, e). a, b ve e represent the smallest possible value, the most promising value and the largest possible value, respectively. Several methods can be employed to implement both methods. The algorithms employed in this study are outlined below.

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Table 3. Specification of experts

Experts	BBN[(a)]	DC[(b)]	EY[(c)]	Education level	Graduated department	Nationality	Company type
Ex 1	11	Ship operation	11	Graduate	Ship engineering	Turkey	Container shipping
Ex 2	9	Ship operation	14	Graduate	Mechanical engineering	Singapore	Tanker operations
Ex 3	13	Ship operation	16	Graduate	Economy	Greece	Container shipping
Ex 4	8	Ship operation	13	Graduate	Ship engineering	Turkey	Tanker operations
Ex 5	7	Ship chartering	12	Graduate	Business	Singapore	Container shipping
Ex 6	8	Ship operation	11	Graduate	Business	Turkey	Container shipping
Ex 7	12	Ship chartering	13	Ph.D.	Business	Greece	Tanker operations
Ex 8	9	Ship chartering	14	Ph.D.	Business	Turkey	Container shipping

Note(s): [a]Bunker Barge Numbers, [b]Duty in the Company, [c]Experience (Years)
Source(s): Author's own elaboration based on the BSV methodology and experts' permission

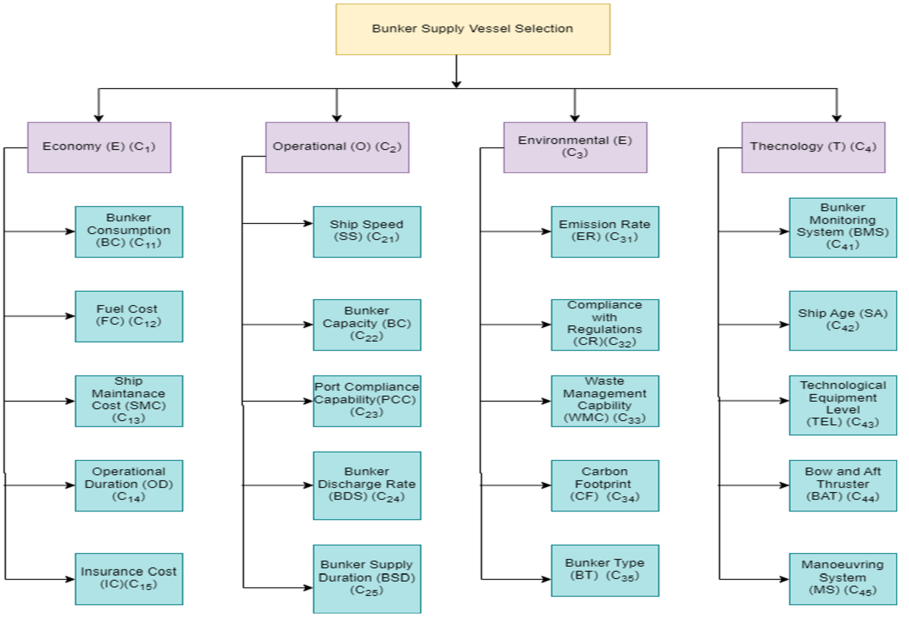


Figure 1. BSV selection hierarchy. Source(s): Author's own elaboration based on the BSVs methodology and expert's opinion

3.1 Fuzzy AHP

The initial step is to construct a hierarchical diagram and a pairwise comparison matrix (A). In this context, it is necessary to define the TFNs to be used in the creation of the pairwise comparison matrix. The TFNs employed in the study are presented in Table 4. The TFNs were defined based on the scale developed by Saaty for the traditional AHP (Saaty, 1980, p. 125).

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Table 4. TFNs based on Saaty's scale (Saaty, 1980)

Scale of saaty	Meaning	Fuzzy triangular scale
1	Same important	(1, 1, 1)
3	Important level weakly	(2, 3, 4)
5	Important level fairly	(4, 5, 6)
7	Important level strongly	(6, 7, 8)
9	Important level very strongly	(9, 9, 9)

Source(s): Author's own elaboration based on the 'Saaty (1980)' Fuzzy AHP methodology

Subsequently, the criterion weights are calculated on the matrix. In this regard, Chang's extended analysis is employed. Let $X = \{x_1, x_2, x_3, \ldots..x_n\}$ be the object set and U $= \{u_1, u_2, , \ldots..u_m\}$ be the target set. Per this analysis, each object is selected, and a coverage analysis is conducted for each target (g_i) (Chang, 1996, p. 31). Consequently, the $M_{gi}^{j}\,(j = 1, 2, \ldots, m)$ dimension analysis values are obtained for each object. The steps of Chang's extended method can be summarised as follows (Chang, 1996, p. 32).

Step 1. The fuzzy synthetic coverage value for each row in the pairwise comparison matrix A is calculated as follows ($i = 1, 2, \ldots., k, n$)

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

In this context, S_i represents the value of the fuzzy synthetic coverage associated with the $S_i th$ criterion.

Step 2. S_i, The magnitudes of S_i's relative to each other are determined.

$$\begin{aligned} &\mathcal{V}(S_1 \geq S_2, S_3, \ldots., S_k, S_n);\ \mathcal{V}(S_2 \geq S_1, S_3, \ldots., S_k, S_n);\ \ldots\ldots\ldots\ldots; \\ &\mathcal{V}(S_n \geq S_1, S_2, S_3, \ldots., S_k) \end{aligned} \tag{2}$$

That is, if $M_1 = (a_1, b_1, e_1)$ and $\mathrm{M}_2 = (a_2, b_2, e_2)$ are two TFNs, then the magnitude of M_1 with respect to M_2 is defined as follows.

$$\mathcal{V}(M_2 \geq M_1) = hgt\,(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & if\ b_2 \geq b_1 \\ 0, & if\ a_1 \geq e_2 \\ \dfrac{a_1 - e_2}{(b_2 - e_2) - (b_1 - a_1)}, & otherwise \end{cases} \tag{3}$$

Here, hgt is the height, and d is the ordinate of the highest intersection point between μ_{M_1} and μ_{M_2}. $\mu_{M_2}(d)$ is the membership function of the intersection of triangular and convex fuzzy numbers.

Step 3. The weight vector W' is determined as follows.

$$W' = (d'(c_1), d'(c_2), \ldots., d'(c_n))^T\ (i = 1, \ldots, n) \tag{4}$$

Here, $d'(c_i)$ shows the weight of the $i - th$ criterion and is determined as follows.

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$$d'(c_1) = \min \mathcal{V}(S_1 \geq S_2, S_3, \ldots., S_k, S_n)\,;\; d'(c_2) = \min \mathcal{V}(S_2 \geq S_1, S_3, \ldots., S_k, S_n);$$

$$d'(c_n) = min\, \mathcal{V}(S_n \geq S_1, S_2, S_3, \ldots., S_k) \tag{5}$$

Step 4. Finally, the normalized weight vector W is obtained by normalization.

$$W = (d(c_1), d(c_2), \ldots .d(c_n))^T \tag{6}$$

3.2 Fuzzy TOPSIS

The characteristics of BSVs are outlined in Appendix A, which presents the 20 sub-criteria used to assess them. The method developed by Chen (2000) was employed to determine the BSV ranking scores. The linguistic variables and TFNs employed in this context are presented in Table 5.

The steps of fuzzy TOPSIS using Chen's method can be summarized as follows.

Step 1. The construction of decision matrix D is based on the utilisation of linguistic variables. In this matrix, the rows correspond to BSV alternatives ($l = 1, 2, \ldots., p$) and the columns correspond to criteria ($i = 1, 2, \ldots., n$). The $\tilde{x}_{li}$ element of the matrix indicates the value of the $l - th$ ship concerning the $i - th$ criterion. Subsequently, the linguistic variables are transformed into the corresponding TFNs (a_{li}, b_{li}, e_{li}) (Yang *et al.*, 2011, p. 14530).

Step 2. To construct the normalised fuzzy decision matrix R, the decision matrix D is standardized in accordance with the following equations.

$$\tilde{r}_{li} = \left(\frac{a_{li}}{e_i^*}, \frac{b_{li}}{e_i^*}, \frac{e_{li}}{e_i^*}\right), i \in B \tag{7}$$

$$\tilde{r}_{li} = \left(\frac{a_i^-}{e_{li}}, \frac{a_i^-}{b_{li}}, \frac{a_i^-}{a_{li}}\right), i \in C \tag{8}$$

$$e_i^* = Maksimum_l\, e_{li} \quad i \in B, a_i^- = Minimum_l\, a_{li} \quad i \in C \tag{9}$$

In this context, the letter B represents the benefit criteria, while the letter C represents the cost criteria.

Step 3. The weighted normalised fuzzy matrix V is calculated in accordance with the following procedure.

Table 5. Verbal variables and TFNs according to Chen's method (Chen, 2000, p. 6)

Verbal variables	TFNs
Very bad (VB)	(0, 0, 1)
Bad (B)	(0, 1, 3)
Slightly bad (SB)	(1, 3, 5)
Moderate (M)	(3, 5, 7)
Slightly good (SG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very good (VG)	(9, 10, 10)

Source(s): Author's own elaboration based on the "Chen (2000)" Fuzzy TOPSIS methodology

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$$V = RW \tag{10}$$

In this context, the symbol W represents the weight vector of the criteria.

Step 4. For each criterion in the weighted normalized fuzzy matrix V, the fuzzy positive ideal $(\tilde{A}^{+})$ solution sets and the fuzzy negative ideal $(\tilde{A}^{-})$ solution sets are determined.

$$\tilde{A}^{+} = \left(\tilde{v}_{l1}^{+}, \tilde{v}_{l2}^{+}, ..., \tilde{v}_{ln}^{+}\right) \quad \tilde{A}^{-} = \left(\tilde{v}_{l1}^{-}, \tilde{v}_{l2}^{-}, ..., \tilde{v}_{ln}^{-}\right) \tag{11}$$

Step 5. The distances of each alternative to $\tilde{A}^{+}$ and $\tilde{A}^{-}$ are calculated using the vertex method. In the equations, Q_l^{+} represents the distance to the $l-th$ BSV positive ideal solution and Q_l^{-} represents the distance to the negative ideal solution.

$$Q_l^{+} = \sum_{i=1}^{n} d\left(\tilde{v}_{li}, \tilde{v}_{li}^{+}\right) \quad l = 1, 2, ..., p \tag{12}$$

$$Q_l^{-} = \sum_{i=1}^{n} d\left(\tilde{v}_{li}, \tilde{v}_{li}^{-}\right) \quad l = 1, 2, ..., p \tag{13}$$

Step 6. The $l-th$ BSV ranking score is calculated as follows.

$$CC_l = \frac{Q_l^{-}}{\left(Q_l^{+} + Q_l^{-}\right)}, \quad l = 1, 2, ..., p \tag{14}$$

and all BSV alternatives are sorted from largest to smallest according to their CC_l values.

3.3 Determination of performance levels of BSVs

The performance levels of BSVs are determined by clustering them according to their fuzzy TOPSIS ranking scores. In this context, in accordance with the acceptability conditions established for ranking scores by Chen *et al*. (Chen *et al*., 1992, p. 261), BSVs with a CC_l value of less than 0.4 are assumed to exhibit a markedly deficient performance level (B). Conversely, BSVs with a CC_l) value of 0.4 and above are classified into three performance levels: good (G), medium (M) and bad (B).

In the case of BSVs with a CC_l value of 0.4 or above, the ranking score ranges and performance levels are determined in accordance with the highest-ranking score within the group. In other words, the BSV with the highest-ranking score within the group is the best-performing BSV (Arıcan and Kara, 2024, p. 11). Subsequently, the remaining BSVs are grouped according to the discrepancy between their scores and those of the highest-performing ship. A 10% margin of error is permitted to ascertain the BSVs exhibiting a medium or superior performance level. In this context, the ranking score ranges and performance levels for BSVs with a CC_l value of 0.4 and above are presented in Table 6. In the following expressions, CC_l represents the ranking score of the l-th ship, whereas $\boldsymbol{CC_l^{\Theta}}$ denotes the highest-ranking score in the group.

4. Results and discussion

The relative weights of the principal criteria, as determined through the application of fuzzy AHP, are presented in Table 7. The results indicate that the criterion of economy has the highest relative weight, with a value of 0.2874. The lowest relative weight is attributed to the environmental criterion, with a value of 0.1996.

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Table 6. The ranking score ranges correspond to the performance levels

The ranking score ranges	Performance levels
$CC_l^* \leq CC_l < (CC_l^{\Theta} - 0,05\,CC_l^{\Theta})$	Good (G)
$(CC_l^* - 0,05\,CC_l^{\Theta}) \leq CC_l < (CC_l^{\Theta} - 0,1CC_l^{\Theta})$	Medium (M)
$CC_l \leq (CC_l^{\Theta} - 0,1CC_l^{\Theta})$	Bad (B)

Source(s): Author's own elaboration based on the BSV methodology and "Arıcan and Kara (2024)" Performance Level Scale

Table 7. The relative weights of the main criteria

Principle criteria	Relative weights
Economy (E)	0.2874
Operational (O)	0.2623
Environmental (E)	0.1996
Technology (T)	0.2507

Source(s): Created by author

Table 8 illustrates the relative weights of the sub-criteria and the overall relative weights. The overall relative weight of each criterion is obtained by multiplying its own relative weight by the relative weight of the main criterion. In terms of overall relative weight, the bunker cost criterion is the most significant, with a value of 0.089. Bunker consumption represents the second most significant sub-criterion, with a relative weight of 0.077. Other criteria with relative weights exceeding 0.5 are ship age, bunker capacity, technological equipment level, bunker discharge rate, bunker supply duration, bow and aft thrusters and ship speed. Insurance costs and waste management capabilities are the two least significant sub-criteria, with a weight of 0.034.

The ranking scores of the BSV ship alternatives are presented in Table 9, as calculated using the fuzzy TOPSIS method. Furthermore, the performance levels of the ships are indicated according to their ranking scores. Two ships have been identified as performing well. These are identified as A6 and A2. Four ships are situated at the medium level. The remaining ships are A7, A8, A4 and A5. The vessels exhibiting the least favourable performance are A3, A10, A1 and A9. Regarding the operation of bunker ships, two alternatives were identified as being suitable in accordance with the established criteria.

The selection of the most suitable BSV requires the evaluation of several criteria and sub-criteria that reflect the vessel's performance across a range of dimensions, including economic, operational, environmental and technological factors. The relative importance of these criteria is indicated in Table 8, thereby facilitating a comprehensive comparison of the alternatives in terms of their respective strengths and weaknesses in specific areas. These sub-criteria are of great importance in understanding why certain vessels perform better than others in specific contexts.

The economy exerts a considerable influence on the overall viability of BSV. Among the economic sub-criteria, fuel cost (c12) is the most influential, with a relative weight of 0.31 and an overall relative weight of 0.089. Consequently, it can be considered the most important factor in the economic category. This is to be expected, given that fuel costs have a direct impact on the operational profitability of a vessel. The top-performing vessels, A6 and A2, also have very good fuel cost management, which in turn plays a significant role in their high overall scores. The second most critical economic sub-criterion is bunker consumption (c11), with a relative weight of 0.27 (overall 0.077). This criterion plays the role of highlighting the

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Table 8. The relative weights and overall relative weights of sub-criteria

Sub-criteria		Relative weights	Overall relative weights
Economy			
c_{12}	Fuel cost (FC)	0.31	0.089
c_{11}	Bunker consumption (BC)	0.27	0.077
c_{13}	Ship maintenance cost (SMC)	0.16	0.045
c_{14}	Operational cost (OC)	0.14	0.040
c_{15}	Insurance cost (IC)	0.12	0.034
Operational			
c_{22}	Bunker capacity (BC)	0.22	0.057
c_{24}	Bunker discharge rate (BDR)	0.21	0.055
c_{25}	Bunker supply duration (BSD)	0.208	0.054
c_{21}	Ship speed (SS)	0.192	0.050
c_{23}	Port compliance capability (PCC)	0.17	0.044
Environmental			
c_{34}	Carbon footprint (CF)	0.228	0.045
c_{31}	Emission rate (ER)	0.22	0.043
c_{35}	Bunker type (BT)	0.201	0.040
c_{32}	Compliance with regulations (CR)	0.179	0.035
c_{33}	Waste management capability (WMC)	0.172	0.034
Technology			
c_{42}	Ship age (SA)	0.235	0.058
c_{43}	Technological equipment level (TEL)	0.226	0.056
c_{44}	Bow and aft thruster (BAT)	0.215	0.053
c_{41}	Bunker monitoring system (BMS)	0.175	0.043
c_{45}	Manoeuvring system (MS)	0.149	0.037

Source(s): Created by author

Table 9. The ranking of ship alternatives

SA[a]	Score	PL[b]
A6	0.8321	G
A2	0.7968	
A7	0.7425	M
A8	0.7061	
A4	0.6978	
A5	0.6897	
A3	0.6799	B
A10	0.6622	
A1	0.6563	
A9	0.6541	

Note(s): [a]Ship Alternatives, [b]Performance Level
Source(s): Created by author

significance of fuel efficiency in long-term operations. The vessels that have achieved the highest ranks, particularly A6, exhibit lower consumption of bunker fuel, thereby improving their overall cost-effectiveness.

Other economic factors, such as the maintenance cost of ship (c13) (0.16), cost of operation (c14) (0.14) and cost of insurance (c15) (0.12), are also of critical importance, albeit with a comparatively lesser weight. These sub-criteria reflect other cost variables that vary among the

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ship alternatives. For instance, A1 and A9 have extremely high costs of maintenance and insurance, which translate to their lower ranking than A6 and A2. It is of prime importance that BSV be in a position to serve the maritime industry needs in an efficient manner, and this is feasible only when the operational performance is maximized. The most influential operational sub-criterion is that of bunker capacity (c22), for which a relative weightage has been allocated 0.22 (total 0.057). This is a sign of the capacity of the ship to transport heavy quantities of fuel, which is directly connected with the frequency and duration of resupply operations. A6 and A7 are some of the vessels in this category, with high bunker capacity, that are particularly noteworthy.

The following key operational factors are bunker discharge rate (c24) (0.21) and bunker supply duration (c25) (0.208), which exert a significant influence on the speed and efficiency with which a vessel can deliver fuel. Furthermore, A6 is the leading vessel in these categories due to its high discharge rate and short supply duration, which makes it one of the most efficient vessels for bunker operations. Vessels with lower bunker capacities, such as A1 and A9, encounter difficulties in this domain, as their extended supply durations and slower discharge rates render them less efficient. Additionally, ship speed (c21) (0.192) and port compliance capability (c23) (0.17) are also significant factors, though with slightly lower weights. These factors impact a vessel's overall operational efficiency and its capacity to comply with regulatory requirements in different ports. A6 and A2 perform well in these areas, thereby further contributing to their high overall rankings.

Environmental sustainability is increasingly being an element considered during ship selection due to new legislation and overall global efforts towards reducing emissions. The most influential environmental sub-factor is the carbon footprint (c34), where the relative weighting is 0.228 (total 0.045). Ship categories A6 and A2, which run cleaner fuels like LNG, are highly rated in this category, as their reduced carbon emissions align with the vision of the industry to be sustainable. Emission rate (c31) (0.22) and bunker type (c35) (0.201) also play a vital role when it comes to deciding the environmental influence of a ship. Ships that use heavy fuel oil (HFO), like A3 and A7, are disadvantaged in this respect because they have higher emissions. These ships are lower rated overall because of their relatively negative environmental impact than ships like A6.

In addition, regulatory compliance (c32) (0.179) and waste management capability (c33) (0.172) are used to reflect the capacity of a ship to meet the environmental requirements and manage operational waste effectively. These sub-criteria are employed to separate environmentally friendly ships from the others. A6 and A2 ships possess excellent performance in these aspects, whereas A3 and A7 ships possess undesirable outcomes, which explain their comparatively lower environmental performance scores.

Technological innovation is an important sub-criterion for improving operational effectiveness and safety in the bunker supply business. The most important technological sub-criterion is ship age (c42) with a relative weight of 0.235 (total 0.058), which serves to highlight the advantages of newer ships. Newer ships have more advanced technology, are more fuel-efficient, and have lower maintenance expenses. Ship A6 stands out because of its sleek line construction and the integration of advanced technology, both of which are contributing factors in ranking it very highly overall. The technological equipment level (c43) (0.226) and bow and aft thrusters (BAT) (c44) (0.215) are also pivotal in determining the vessel's capacity to manoeuvre efficiently and utilise contemporary equipment for fuel delivery. A6, equipped with advanced manoeuvring systems and technology, is the highest-ranking vessel in this area, while older vessels like A4 and A5 lag due to their age and outdated technology.

The bunker monitoring system (BMS) (c41) (0.175) and the manoeuvring system (MS) (c45) (0.149) are also of importance, though they carry slightly less weight. These sub-criteria ensure operational safety and efficiency. Vessels such as A6 and A2 perform well due to their advanced monitoring and manoeuvring systems. Vessels of an older generation, such as A1 and A9, are less technologically advanced and consequently achieve lower overall scores.

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4.1 Real-world contextualization

In a Rotterdam port scenario, A6's high discharge rate and LNG compatibility reduced bunkering time by 15% compared to A3, a heavy fuel oil vessel, aligning with port demands for efficiency and sustainability. This case study demonstrates the framework's applicability, where A6's strengths (e.g. 0.8321 score) match real-world needs for quick turnarounds and IMO compliance.

4.2 Sensitivity analysis

To test ranking robustness, environmental criterion weights were increased by 10% (e.g. environmental from 0.1996 to 0.2196). Table 10 shows adjusted rankings, with A6 and A2 retaining top spots due to their low carbon footprints, while A3 and A7 drop further due to higher emissions.

BSV selection must balance economic viability, operational efficiency, environmental responsibility and technological advancement. Practically, shipping companies can train operators to optimize discharge rates, as A6 demonstrates. Policy-wise, port authorities should incentivize LNG-compatible BSVs to meet IMO's 2030 carbon reduction targets, supported by the sensitivity analysis favouring low-emission vessels like A6 and A2.

A comparison of this study with other ship selection studies reveals both similarities and differences, particularly regarding the multi-criteria decision-making (MCDM) methods employed and the diversity of selection criteria. Studies such as those conducted by Aymelek *et al*. (2014, p. 770) and De *et al*. (2021, p. 931), which focus on fuel management and the use of LNG as a ship fuel, exhibit similarities with this study with respect to economic criteria (e.g. fuel consumption and operational costs). However, this study is distinguished from the others by placing greater emphasis on the sub-criteria of technology and the environment. For instance, the evaluation of carbon footprint and waste management capability is consistent with the findings of Mazraati (2011, p. 433) and Lam *et al*. (2011, p. 199), yet the relative importance assigned to these criteria differs from the approach proposed by Görçün and Küçükönder (2021).

Furthermore, this study's utilisation of the FAHP and FTOPSIS hybrid method differentiates it from traditional MCDM techniques, such as those proposed by Chen and Hwang (1992). This approach offers a more contemporary and sophisticated methodology for addressing complex decision-making challenges. However, they are compared with the additive ratio assessment (ARAS) technique proposed by Zavadskas and Turskis (2011). The technique used by Görçün (2022) and Zolfani *et al*. (2022) in the methodology and using Type-2 neutrosophic fuzzy sets brings innovative methods towards handling uncertainty. This current study, in comparison with both the aforementioned methodologies, is designed to

Table 10. Sensitivity analysis with 10% increased environmental weight

SA(e)	Original score	Adjusted score	PL(f)
A6	0.8321	0.8456	G
A2	0.7968	0.8102	G
A7	0.7425	0.7253	M
A8	0.7061	0.6987	M
A4	0.6978	0.6891	M
A5	0.6897	0.6804	M
A3	0.6799	0.6621	B
A10	0.6622	0.6543	B
A1	0.6563	0.6489	B
A9	0.6541	0.6457	B

Source(s): Created by author

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maintain economic as well as technical balance. Besides, focusing on technological levels and ship manoeuvring abilities is consistent with approaches followed by Emovon (2016) and Dos Santos *et al*. (2021), though differing by relative significance.

The assessment of the sub-criteria along the economic, operational, environmental, and technological dimensions places A6 in the lead among BSVs, closely followed by A2. A6 excels because of a number of desirable features, including high fuel consumption efficiency, high bunker capacity, fast discharging rate, low carbon footprint and state-of-the-art equipment. A2 itself performs well in all these features but falls behind A6 in the dimension of state-of-the-art equipment.

In contrast, vessels such as A1, A3 and A9 are less competitive due to increased fuel consumption, reduced bunker capacity, worse environmental performance and older technology. Therefore, these factors render them less suitable for operations that prioritize cost-effectiveness, environmental sustainability and advanced technological capabilities.

The assessment of the sub-criteria along the economic, operational, environmental and technological dimensions places A6 in the lead among BSVs, closely followed by A2. A6 excels because of a number of desirable features, including high fuel consumption efficiency, high bunker capacity, fast discharging rate, low carbon footprint and state-of-the-art equipment. A2 itself performs well in all these features but falls behind A6 in the dimension of state-of-the-art equipment.

In contrast, vessels such as A1, A3 and A9 are less competitive due to increased fuel consumption, reduced bunker capacity, worse environmental performance and more antiquated technology. Therefore, these factors render them less suitable for operations that prioritize cost-effectiveness, environmental sustainability and advanced technological capabilities.

The selection of a BSV must therefore consider the relative order of each criterion with the view to achieving a reasonable balance among economic performance, operating efficiency, environmental responsibility and technological advancements with a view to achieving optimal results in fuel supply operations.

5. Conclusion

This study employs fuzzy-AHP and fuzzy-TOPSIS methods to identify bunker supply vessels (BSVs) and closely analyse their outcomes, reflecting their primary role in maritime shipping by influencing operating costs, efficiency and environmental sustainability. Analysing ten BSV alternatives across 20 sub-criteria, the study identified fuel efficiency, operating costs and maintenance ease as the most significant factors, reflecting the necessity for the maritime industry to be cost-efficient and sustainable. The hybrid multi-criteria decision method simplifies decision-making on confusing matters, offering a useful instrument to be considered both in the context of academic research as well as practical application. Management should recommend the implementation of training to further maximize BSV discharge efficiency levels, such as A6 verifies achieving, while the government should encourage LNG-equipped BSVs towards alignment with IMO's 2030 carbon goals within the trend followed by high-achievers like A6 and A2. Despite the above findings, the limitation in this study include sample size and application of expert opinion, potentially introducing personal judgements that affect reliability. Future studies can overcome these by surveying more BSVs and criteria, integrating machine learning with MCDM to conduct predictive analysis or looking into blockchain in order to gain more visibility over the bunker supply chain, ultimately achieving broader, generalizable results that enable sustainable maritime logistics.

Supplementary material

The supplementary material for this article can be found online.

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