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DEVELOPMENT OF A FUZZY-BASED DECISION SUPPORT SYSTEM FOR SUSTAINABLE TRACTOR SELECTION IN GREEN PORTS

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Abstract. *Tractors play a critical role in the operational processes of green ports. The primary objective of this study is to develop a decision support system (DSS) for the selection of tractors suitable for green port operations. In this context, a hybrid multi-criteria decision-making (MCDM) approach based on fuzzy logic—namely the FF-Hamacher-CIMAS-LODECI-RADAR (Fermatean Fuzzy–Hamacher-Criteria Importance Assessment-Logarithmic Decomposition of Criteria Importance- Ranking based on the Distances and Range) hybrid method is proposed. This hybrid model enables the simultaneous integration of both quantitative and qualitative criteria into the decision-making process. Expert weight vectors are determined using Fermatean fuzzy sets, while the overall criteria weight vector is constructed through a combination of subjective (FF-Hamacher-CIMAS) and objective (FF-Hamacher-LODECI) weighting techniques. The performance ranking of tractor alternatives is obtained using the RADAR method. The proposed methodology was applied to a tractor selection problem for a green port in Türkiye. The decision model was established based on the evaluations of ten experts, involving eight criteria (two quantitative and six qualitative) and five alternative tractors. According to the results of the case study, Towing Capacity emerged as the most influential criterion. Among the alternatives, the MAFI T 230e tractor demonstrated the highest performance. The robustness of the proposed hybrid method was supported through three sensitivity analysis scenarios. Additionally, comparative analyses revealed a high level of consistency in the results, confirming the reliability of the method. Based on the findings, practical implications and recommendations were provided to support decision-making processes in green port operations.*

Key words: *Tractor selection, Fermatean Fuzzy sets, FF-Hamacher-CIMAS, FF-Hamacher-LODECI, RADAR*

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1. INTRODUCTION

The increasing volume of global trade has placed ports at the center of not only economic growth but also environmental sustainability. The increasing global trade volume also leads to increased greenhouse gas (GHG) and particulate matter (PM) emissions from logistics equipment [1]. Today, ports are not only cargo handling areas; they have also become one of the important sources of GHG emissions with their energy-intensive, fossil fuel-based equipment [2]. Increasing efficiency and reducing environmental impacts in port operations have become both political and economic imperative. Sustainability goals in port operations necessitate the transformation of not only ships but also in-port equipment such as cranes, carrier vehicles and terminal tractors [3]. In this context, terminal tractors play a critical role in the transportation of containers within the terminal and account for a significant portion of port-related emissions [4].

In large commercial ports such as the San Pedro Bay Port Complex in California, terminal tractors contribute to 28% and 33% of total oxides of nitrogen (NO_x) and PM emissions, respectively [5]. As in the case of Ambarlı Port, diesel-fueled terminal tractors produce the highest carbon emissions among in-port equipment [6]. This high contribution rate has placed the conversion of terminal tractors at the center of ports' carbon emission reduction strategies. Regulatory policies and technological advances developed in recent years encourage the replacement of diesel engines with low or zero-emission alternative power systems [7-9].

Traditional diesel engine tractors attract attention with their high fuel consumption and emission production due to the characteristics of in-port operations such as low speed, frequent stop/start and high idle rate [1]. Real field tests have shown that diesel terminal tractors emit 2 to 3 times more NO_x and PM2.5 than their emission certification levels [10].

The evaluation of alternative energy systems has added a new dimension to the selection of terminal tractors. Electric and hydrogen fuel cell tractors promise zero emissions and are also promising in terms of energy efficiency. Studies conducted in recent years reveal that electric versions of terminal tractors offer advantages in terms of both fuel consumption and operating costs [11]. Comparative total cost of ownership analyses show that hydrogen fuel cell tractors will be cost-competitive with their diesel counterparts [1]. Thanks to adaptive energy management systems designed specifically for variable load profiles, these vehicles provide efficient energy consumption and operational flexibility [12].

The technological transition process affects not only environmental but also operational decisions. Studies conducted in port terminals have shown that optimal planning and task assignment strategies of terminal tractors can significantly reduce loading/unloading times and empty trip rates [13]. In addition, evaluation of various transfer scenarios with different tractor models (e.g. semi-trailer or full trailer) once again emphasizes the importance of flexibility and engineering standards in equipment selection [14].

The primary motivation of this study is to develop a decision support system (DSS) for the selection of tractors used in green ports. The main objective is to address the tractor selection problem through a multi-criteria decision-making (MCDM) approach by proposing a hybrid method as a DSS. To handle complex and sensitive computations, the use of Fermatean Fuzzy (FF) sets [15], which are based on fuzzy logic, is proposed. FF sets not only offer enhanced capability in managing high levels of uncertainty but also allow for more flexible expression of expert judgments.

Moreover, to strengthen the operations and aggregation processes of FF sets, Hamacher t-norm and t-conorm-based FF sets have been utilized as Bonferroni aggregation [16]. Specifically, the FFHWA (Fermatean fuzzy Hamacher weighted average) aggregation operator [17] was employed for aggregating expert evaluations. The proposed hybrid DSS is the FF-Hamacher-CIMAS-LODECI-RADAR (FF- Hamacher-Criteria Importance Assessment-Logarithmic Decomposition of Criteria Importance) method. In this framework, FF-Hamacher-CIMAS is adopted as the subjective criteria weighting method, where the CIMAS technique [18] is adapted to the FF-Hamacher environment for the first time. For objective criteria weighing, the FF-Hamacher-LODECI method was developed by extending the LODECI method [19] using FF-Hamacher sets. Both weighting methods incorporate FF-Hamacher sets for the first time in literature.

The FF-Hamacher-CIMAS method was chosen due to its ability to provide consistency-based weighting calculations, whereas the FF-Hamacher-LODECI method offers precise weight computations based on logarithmic decomposition. For ranking the tractor alternatives, the RADAR method [20] was utilized. The proposed hybrid model enables the simultaneous evaluation of both quantitative and qualitative criteria, and the ranking process is performed using the RADAR approach [21]. The applicability, robustness, and consistency of the proposed hybrid method were validated through a real-world case study conducted at a green port in Türkiye.

This study presents a novel DSS for selecting the most suitable tractor for green port operations by integrating fuzzy logic and MCDM techniques. A new hybrid methodology (FF-Hamacher-CIMAS-LODECI-RADAR) is proposed, combining subjective and objective weighting methods with an advanced ranking model. Subjective weights are derived using FF-Hamacher-CIMAS to reflect expert judgments, while objective weights are calculated through FF-Hamacher-LODECI based on decision matrix data. The model evaluates both quantitative (Towing Capacity, Turning Radius) and qualitative (Energy Efficiency, Emission Level, Maintenance Cost, Total Cost of Ownership, Ease of Use, Port Infrastructure Suitability) criteria simultaneously. Applied to a real-world case in Türkiye involving five tractor alternatives and ten experts, the MAFI T 230e emerged as the top choice, with Towing Capacity as the most critical criterion. The methodology's robustness was confirmed through sensitivity analysis and comparison with 15 established MCDM methods, showing high consistency. This research contributes both methodologically and practically to sustainable decision-making in green port logistics and beyond.

This paper is structured into six sections. Section 2 presents the literature review. Section 3 outlines the methodology adopted in the study. Section 4 details the case study conducted to demonstrate the applicability of the proposed approach. Section 5 discusses the results and their practical implications. Finally, Section 6 provides the conclusions drawn from the study.

2. Literature Review

2.1 Green Ports: A Paradigm for Sustainable Port Management

Green ports represent a strategic approach aimed at mitigating environmental impacts while enhancing energy efficiency and sustainable management practices within port operations. Traditional port activities often contribute significantly to environmental externalities, including elevated GHG emissions, and air and water pollution. Consequently, there is an imperative for ports to adopt sustainable practices to address these challenges effectively.

The operational components of ports, such as terminal equipment, ships, and land transportation systems, are primary sources of carbon emissions and pollutants, thereby impacting air quality. Various global ports have undertaken concerted efforts to implement emission reduction measures, with outcomes influenced by factors such as population density, business models, and specialization in container transportation [22].

Effective collaboration between public authorities and port administrations is pivotal in implementing policy instruments aimed at reducing GHG emissions. Research underscores the role of environmental incentive systems, automation, and digitalization in facilitating the transition towards green port operations, particularly highlighted in Asian ports [23].

Renewable energy technologies, such as solar energy, wind turbines, fuel cells, and ocean energy systems, emerge as promising solutions to diminish fossil fuel dependency in ports. Studies confirm the technical and economic viability of these technologies in significantly reducing carbon emissions and enhancing sustainability [24].

Modeling energy consumption and enhancing the efficiency of port facilities are critical components of operational strategies. It has been demonstrated that optimizing port operations can lead to substantial reductions in energy consumption, with potential savings estimated at up to 34% [25]. Integrating green port initiatives with logistics efficiency further underscores the potential for reducing carbon emissions and operational costs, exemplified by initiatives such as transitioning hazardous material transportation vehicles to electric systems [26].

The advancement of digital technologies plays a transformative role in shaping green ports. Innovations such as Internet of Things (IoT), artificial intelligence (AI), remote monitoring systems, and autonomous technologies are instrumental in optimizing energy consumption, emission control, and logistics management within port environments [27].

In conclusion, the evolution towards green ports necessitates a holistic approach encompassing policy interventions, technological advancements, and collaborative governance to achieve sustainable development goals. By integrating these strategies, ports worldwide can effectively mitigate environmental impacts while fostering economic growth and operational resilience in a rapidly evolving global context.

2.2 Green Ports: A Paradigm for Sustainable Port Management

The vision of green ports fundamentally seeks to minimize the environmental impacts associated with port operations, enhance energy efficiency, and reduce carbon footprints. Within this framework, cargo handling equipment (CHE) represents one of the most significant sources of port-related emissions. Key machinery, including terminal tractors, rubber-tired gantry (RTG) cranes, straddle carriers, forklifts, and reach stackers, are indispensable for maintaining port operational efficiency, yet they concurrently contribute substantially to greenhouse gas emissions and overall energy consumption.

Terminal tractors have been identified as primary contributors to emissions within port environments. Empirical data from Chinese ports reveal that although terminal tractors comprise just over one-third of all equipment in operation, they account for nearly half of the total fuel consumption among CHE [28]. A parallel trend has been observed in Turkish ports, where terminal tractors constitute many carbon emissions within CHE fleets [6].

These findings highlight the critical need to reconsider the technological design and environmental impact of such equipment.

The energy consumption profile of CHE is influenced by multiple factors, including fuel type, engine specifications, and operational duty cycles. Notably, equipment with larger engine capacities (though fewer in number) may disproportionately contribute to emissions due to prolonged operational hours or intensive workload demands [28]. This recognition has catalyzed accelerated efforts toward the electrification of port equipment, particularly in regions with stringent policy frameworks or explicit carbon reduction targets.

The transition to electric or hybrid CHE alternatives presents several challenges. Research conducted in California ports identifies key barriers such as high upfront investment costs, limitations in grid capacity, and the need for workforce adaptation [29]. Nonetheless, with strategic long-term planning, electrification initiatives have demonstrated considerable potential not only to reduce emissions but also to modernize port infrastructure in a manner that promotes inclusivity and resilience [30].

Beyond technological substitution, optimizing the deployment and scheduling of CHE is critical for reducing emissions and improving operational efficiency. Coordinated scheduling among terminal tractors, cranes, and yard vehicles can significantly reduce idle times, lower energy consumption, and enhance overall system productivity. Emerging optimization frameworks have demonstrated effectiveness in integrating various types of equipment within unified planning routines, thereby reducing empty trips and operational delays [31-32].

The selection of cargo handling equipment is a strategic element within sustainable port management. MCDM methodologies, such as the AHP, PROMETHEE, and TOPSIS, are extensively employed to evaluate alternative equipment based on a comprehensive set of criteria. These criteria typically encompass environmental factors (e.g., CO_2, NOx, particulate matter emissions), economic considerations (investment and operational costs), technical specifications (power output, efficiency), and operational characteristics (flexibility, cycle time) [33].

In summary, the progression toward green ports necessitates a dual focus on mitigating the environmental footprint of cargo handling equipment and enhancing their operational efficiency. Key strategies include the electrification of high-emission equipment (particularly terminal tractors) the integration of these assets within optimized scheduling models, and the adoption of life-cycle management approaches. Collectively, these measures constitute essential components for achieving long-term sustainability and environmental stewardship in port operations.

3. METHODOLOGY

3.1 Hamacher T-Norm and T-Conorm based Aggregation Operator

Definition 1. The FF set $(\tilde{\mathcal{F}})$ defined as $\tilde{\mathcal{F}} = \{\langle f, x_{\tilde{\mathcal{F}}}(f), y_{\tilde{\mathcal{F}}}(f) \mid f \in F\rangle\}$ is a fuzzy logic-based set using functions defined by the universe F and element f. The FF numbers defined in this set are defined as follows: $x_{\tilde{\mathcal{F}}}(f)$: the degree of membership, $y_{\tilde{\mathcal{F}}}(f)$: the degree of non-membership, and $\left(z_{\tilde{\mathcal{F}}}(f)\right)$: the indeterminacy degree. The FF numbers fulfill the following conditions: $0 \le \left(x_{\tilde{\mathcal{F}}}(f)\right)^3 + \left(y_{\tilde{\mathcal{F}}}(f)\right)^3 \le 1$ and $z_{\tilde{\mathcal{F}}}(f) = \sqrt[3]{1 - \left(x_{\tilde{\mathcal{F}}}(f)\right)^3 - \left(y_{\tilde{\mathcal{F}}}(f)\right)^3}$ [15].

Definition 2. The accuracy function is calculated when the score functions used to convert FF sets into numerical values are equal. Consider two FF sets as $\tilde{\mathcal{F}}_1 = \left\{\langle f, x_{\tilde{\mathcal{F}}_1}(f), y_{\tilde{\mathcal{F}}_1}(f) \mid f \in F\rangle\right\}$ and $\tilde{\mathcal{F}}_2 = \left\{\langle f, x_{\tilde{\mathcal{F}}_2}(f), y_{\tilde{\mathcal{F}}_2}(f) \mid f \in F\rangle\right\}$. Score function $\left(Sc\left(\tilde{\mathcal{F}}_1\right)\right)$ calculation is shown in Eq. (1) and accuracy function $\left(Ac\left(\tilde{\mathcal{F}}_1\right)\right)$ calculation is shown in Eq. (2) [15]:

$$Sc\left(\tilde{\mathcal{F}}_1\right) = \frac{1}{2}\left(1 + \left(x_{\tilde{\mathcal{F}}_1}(f)\right)^3 - \left(y_{\tilde{\mathcal{F}}_1}(f)\right)^3\right) \tag{1}$$

$$Ac\left(\tilde{\mathcal{F}}_1\right) = \left(x_{\tilde{\mathcal{F}}_1}(f)\right)^3 + \left(y_{\tilde{\mathcal{F}}_1}(f)\right)^3 \tag{2}$$

Definition 3. The Hamacher t-norm and t-conorm are computed by applying Eq. (3) and Eq. (4) respectively [17]:

$$T - norm\ (a,b) = \frac{ab}{\vartheta + (1-\vartheta)(a+b-ab)} \tag{3}$$

$$T - conorm\ (a,b) = \frac{a+b-ab-(1-\vartheta)ab}{1-(1-\vartheta)ab} \tag{4}$$

herein, $a, b \in [0,1]$ and $\vartheta > 0$.

Definition 4. For a group of FF sets defined as $\tilde{\mathcal{F}}_r = \left\{\langle f, x_{\tilde{\mathcal{F}}_r}(f), y_{\tilde{\mathcal{F}}_r}(f) \mid f \in F\rangle\right\}$, the FFHWA aggregation operator is computed by applying Eq. (5) [17]:

$$FFHWA = \bigoplus_{r=1}^{\mathrm{R}} \tau_r \tilde{\mathcal{F}}_r = \left(\begin{array}{c} \sqrt[3]{\dfrac{\prod_{r=1}^{\mathrm{R}}\left(1+(\vartheta-1)\left(x_{\tilde{\mathcal{F}}_r}(f)\right)^3\right)^{\tau_r} - \prod_{r=1}^{\mathrm{R}}\left(1-\left(x_{\tilde{\mathcal{F}}_r}(f)\right)^3\right)^{\tau_r}}{\prod_{r=1}^{\mathrm{R}}\left(1+(\vartheta-1)\left(x_{\tilde{\mathcal{F}}_r}(f)\right)^3\right)^{\tau_r} + (\vartheta-1)\prod_{r=1}^{\mathrm{R}}\left(1-\left(x_{\tilde{\mathcal{F}}_r}(f)\right)^3\right)^{\tau_r}}}, \\ \dfrac{\sqrt[3]{\vartheta}\prod_{r=1}^{\mathrm{R}}\left(y_{\tilde{\mathcal{F}}_r}(f)\right)^{\tau_r}}{\sqrt[3]{\prod_{r=1}^{\mathrm{R}}\left(1+(\vartheta-1)\left(1-\left(y_{\tilde{\mathcal{F}}_r}(f)\right)^3\right)\right)^{\tau_r} + (\vartheta-1)\prod_{r=1}^{\mathrm{R}}\left(y_{\tilde{\mathcal{F}}_r}(f)\right)^{3\tau_r}}} \end{array}\right) \tag{5}$$

3.2 The Novel FF-Hamacher-CIMAS- LODECI-RADAR Hybrid Method

In this study, the elements of the decision model are defined as experts $\left(E = \{\epsilon_1, \epsilon_2, \ldots, \epsilon_{\text{ě}}, \ldots, \epsilon_{\text{Ě}}\}\ (\text{ě} = 1,2, \ldots, \text{Ě})\right)$, quantitative criteria $\left(N = \{\eta_1, \eta_2, \ldots, \eta_{\text{ň}}, \ldots, \eta_{\text{Ň}}\}\ (\text{ň} = 1,2, \ldots, \text{Ň})\right)$, qualitative criteria $\left(L = \{\text{ƚ}_1, \text{ƚ}_2, \ldots, \text{ƚ}_{\text{ĺ}}, \ldots, \text{ƚ}_{\text{Ĺ}}\}\ (\text{ĺ} = 1,2, \ldots, \text{Ĺ})\right)$, overall criteria $\left(T = \left\{\text{ŧ}_1, \text{ŧ}_2, \ldots, \text{ŧ}_{\text{ţ}}, \ldots, \text{ŧ}_{\text{Ţ}}\right\}\ (\text{ţ} = 1,2, \ldots, \text{Ţ});\ (\text{Ň} + \text{Ĺ} = \text{Ţ})\right)$, and alternatives $\left(A = \left\{a_1, a_2, \ldots, a_{\text{ą}}, \ldots, a_{\text{Ą}}\right\}\ (\text{ą} = 1,2, \ldots, \text{Ą})\right)$.

The hybrid method consists of four stages: Stage 1: Subjective criteria weights are determined based on the experts' assessment of all criteria. Expert weights are also determined. Stage 2: Objective criterion weights are determined by experts evaluating only the alternatives according to qualitative criteria and are combined with other quantitative criteria. Stage 3: The criteria obtained because of subjective and objective criteria weighing methods are combined. Stage 4: Based on the final criteria weights, Terminal Tractor for Sustainable Port Management performance levels are calculated and ranked. The diagram of the FF-Hamacher-CIMAS-LODECI-RADAR hybrid method is presented in Fig. 1.

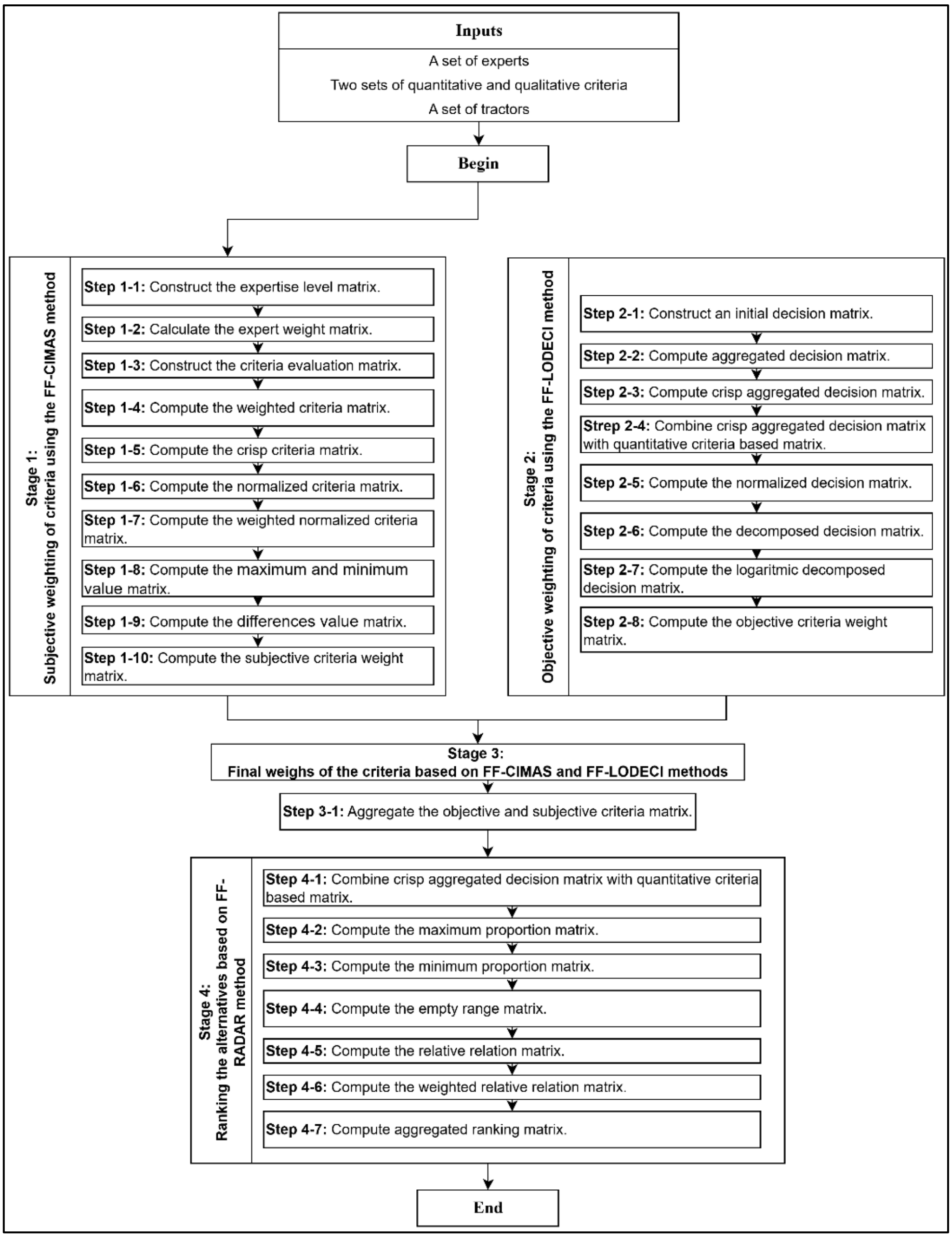

Fig. 1 The diagram of the FF-Hamacher-CIMAS-LODECI-RADAR hybrid method

The application steps of the FF-Hamacher-CIMAS-LODECI-RADAR hybrid method are summarized as follows:

Stage 1: *Subjective weighting of criteria using the FF-CIMAS method* [18]:

Step 1-1: It is important to calculate expert weights according to the levels of expertise, which play an important role in decision-making processes, and to integrate these weights into the decision-making process. In this step, the expertise levels presented in Table 1 are determined and the expertise level matrix $\left(\tilde{B} = [\tilde{B}_{ě}]_{Ě}\right)$ is created accordingly.

Table 1 Linguistic expressions for expertise levels [34]

Linguistic expressions	FFNs
Very-poor (VP)	(0.21, 0.70)
Poor (P)	(0.36, 0.41)
Medium (M)	(0.42, 0.52)
Good (G)	(0.73, 0.10)
Very-good (VG)	(0.82, 0.50)

Step 1-2: The linguistic expressions are transformed into FFNS and after obtaining the score function with Eq. (6), experts' weights are calculated with Eq. (7):

$$\tilde{B}_{ě} = Sc(\tilde{B}_{ě}) = \frac{1}{2}\left(1 + \left(x_{\tilde{B}_{ě}}(f)\right)^3 - \left(y_{\tilde{B}_{ě}}(f)\right)^3\right); Sc(\tilde{B}_{ě}) \in [0,1] \tag{6}$$

$$\Psi_{ě} = \frac{\tilde{B}_{ě}}{\sum_{ě=1}^{Ě} \tilde{B}_{ě}}; \left(ě = 1,2,\dots, Ě\right) \tag{7}$$

Step 1-3: To derive the criteria evaluation matrix, experts $(\epsilon_{ě})$ evaluate each overall criterion $(ƫ_{ţ})$ using the linguistic expressions as presented in Table 2. Then, these linguistic expressions are transformed into FF numbers, and the criteria evaluation matrix $\left(\tilde{Z} = [\tilde{Z}_{ţě}]_{ŢĚ}\right)$ is created.

Table 2 Linguistic expressions for evaluating criteria/alternatives [34]

Linguistic expressions	FFNs
Exceptionally low (ExL)	(0.30, 0.50)
Extremely low (EL)	(0.35, 0.43)
Very low (VL)	(0.36, 0.56)
Low (L)	(0.40, 0.73)
Below average (BA)	(0.42, 0.30)
Average (A)	(0.47, 0.21)
Above average (AA)	(0.50, 0.62)
High (H)	(0.55, 0.38)
Very high (VH)	(0.60, 0.18)
Extremely high (EH)	(0.72, 0.50)
Exceptionally high (ExH)	(0.83, 0.42)

Step 1-4: To derive the weighted criteria evaluation matrix $\left(\widetilde{H} = [\widetilde{H}_{ţě}]_{ŢĚ}\right)$, the expertise level matrix and the criteria evaluation matrix are aggregated via FF-Hamacher product operation (Eq. (8)).

$$\widetilde{H}_{\text{ţĕ}} = \tilde{B}_{\text{ĕ}} \otimes \tilde{Z}_{\text{ţĕ}} =$$

$$\left\{ \left(\left(\frac{x_{\tilde{B}_{\text{ĕ}}}(f)\, x_{\tilde{Z}_{\text{ţĕ}}}(f)}{\sqrt[3]{\vartheta + (1-\vartheta)\left(\left(x_{\tilde{B}_{\text{ĕ}}}(f)\right)^3 + \left(x_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3 - \left(\left(x_{\tilde{B}_{\text{ĕ}}}(f)\right)^3 \left(x_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3 \right) \right)}} \right), \sqrt[3]{\frac{\left(y_{\tilde{B}_{\text{ĕ}}}(f)\right)^3 + \left(y_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3 - \left(\left(y_{\tilde{B}_{\text{ĕ}}}(f)\right)^3 \left(y_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3 \right) - (1-\vartheta)\left(\left(y_{\tilde{B}_{\text{ĕ}}}(f)\right)^3 \left(y_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3 \right)}{1-(1-\vartheta)\left(\left(y_{\tilde{B}_{\text{ĕ}}}(f)\right)^3 \left(y_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3 \right)}} \right) \mid f \in F \right\} \quad (8)$$

Step 1-5: The score function $\left(Sc\left(\widetilde{H}_{\text{ţĕ}}\right)\right)$ used to convert the weighted criteria evaluation matrix into crisp values (Eq. (9)) yields the crisp weighted criteria evaluation matrix $\left(H = \left[H_{\text{ţĕ}}\right]_{\text{ŢĔ}}\right)$.

$$H_{\text{ţĕ}} = Sc\left(\widetilde{H}_{\text{ţĕ}}\right) = \frac{1}{2}\left(1 + \left(x_{\widetilde{H}_{\text{ţĕ}}}(f)\right)^3 - \left(y_{\widetilde{H}_{\text{ţĕ}}}(f)\right)^3\right); \left(Sc\left(\widetilde{H}_{\text{ţĕ}}\right) \in [0,1]\right) \quad (9)$$

Step 1-6: The normalized criteria evaluation matrix $\left(\Lambda = \left[\Lambda_{\text{ţĕ}}\right]_{\text{ŢĔ}}\right)$ is computed applying Eq. (10).

$$\Lambda_{\text{ţĕ}} = \frac{H_{\text{ţĕ}}}{\sum_{\text{ţ}=1}^{\text{Ţ}} H_{\text{ţĕ}}}; \left(\text{ţ} = 1, \dots, \text{Ţ}; \text{ĕ} = 1,2, \dots, \text{Ĕ}\right) \quad (10)$$

Step 1-7: Eq. (11) is used to determine the weighted criteria evaluation matrix$\left(P = \left[P_{\text{ţĕ}}\right]_{\text{ŢĔ}}\right)$.

$$P_{\text{ţĕ}} = \left(\Lambda_{\text{ţĕ}} * \Psi_{\text{ĕ}}\right); \left(\text{ţ} = 1, \dots, \text{Ţ}; \text{ĕ} = 1,2, \dots, \text{Ĕ}\right) \quad (11)$$

Step 1-8: The maximum value matrix $\left(P_{\text{ţ}}^{max} = \left[P_{\text{ţ}}^{max}\right]_{\text{Ţ}}\right)$ is calculated by Eq. (12) and the minimum value matrix $\left(P_{\text{ţ}}^{min} = \left[P_{\text{ţ}}^{min}\right]_{\text{Ţ}}\right)$ is calculated by Eq. (13).

$$P_{\text{ţ}}^{max} = \max_{1 \le \text{ţ} \le \text{Ţ}} P_{\text{ţ}}\,; (\text{ţ} = 1, \dots, \text{Ţ}) \quad (12)$$

$$P_{\text{ţ}}^{min} = \min_{1 \le \text{ţ} \le \text{Ţ}} P_{\text{ţ}}\,; (\text{ţ} = 1, \dots, \text{Ţ}) \quad (13)$$

Step 1-9: The matrix representing the differences between minimum and maximum values $\left(M = \left[M_{\text{ţ}}\right]_{\text{Ţ}}\right)$ is computed applying Eq. (14).

$$M_{\text{ţ}} = \left(P_{\text{ţ}}^{max} - P_{\text{ţ}}^{min}\right); (\text{ţ} = 1, \dots, \text{Ţ}) \quad (14)$$

Step 1-10: The criteria weight matrix $\left(\text{ɰ} = \left[\text{ɰ}_{\text{ţ}}\right]_{\text{Ţ}}\right)$ is computed applying Eq. (15).

$$\text{ɰ}_{\text{ţ}} = \frac{M_{\text{ţ}}}{\sum_{\text{ţ}=1}^{\text{Ţ}} M_{\text{ţ}}}; (\text{ţ} = 1, \dots, \text{Ţ}) \tag{15}$$

herein, $\text{ɰ}_{\text{ţ}} = (\text{ɰ}_1, \text{ɰ}_2, \dots, \text{ɰ}_{\text{Ţ}})$, $\text{ɰ}_{\text{ţ}} \in [0,1]$, and $\sum_{\text{ţ}=1}^{\text{Ţ}} \text{ɰ}_{\text{ţ}} = 1$.

If the (RI)values fall below 0.1, the criteria's weights are consistent, and the next step is taken.

Stage 2: Objective weighting of criteria using the FF-LODECI method [18]

Step 2-1: Each alternative $(a_{\text{ą}})$ is evaluated by each expert $(\epsilon_{\text{ĕ}})$ against attribute criteria only $(\text{ƚ}_{\text{ĺ}})$ using the linguistic expressions defined in Table 2. Following this evaluation, the LVs are transformed into FF sets as detailed in Table 2. Thus, an initial decision matrix $\left(\widetilde{\mathbb{L}}^{(\epsilon_{\text{ĕ}})} = \left[\widetilde{\mathbb{L}}^{(\epsilon_{\text{ĕ}})}{}_{\text{ąĺ}}\right]_{\text{Ą}x\text{Ĺ}}\right)$ where $\widetilde{\mathbb{L}}^{(\epsilon_{\text{ĕ}})}{}_{\text{ąĺ}} = \left(x_{\widetilde{\mathbb{L}}^{(\epsilon_{\text{ĕ}})}{}_{\text{ąĺ}}}(f), y_{\widetilde{\mathbb{L}}^{(\epsilon_{\text{ĕ}})}{}_{\text{ąĺ}}}(f)\right)$ $(\text{ą} = 1,2, \dots, \text{Ą};\ \text{ĺ} = 1,2, \dots, \text{Ĺ};\ \text{ĕ} = 1,2, \dots, \text{Ĕ})$ is created.

Step 2-2: The evaluations made by each expert are combined using the FFHWA aggregation operator shown in Eq. (16). Thus, the aggregated decision matrix $\left(\mathbb{L} = [\mathbb{L}_{\text{ąĺ}}]_{\text{Ą}x\text{Ĺ}}\right)$ is composed.

$$\mathbb{L} = \tilde{B}_{\text{ĕ}} \otimes \tilde{Z}_{\text{ţĕ}} =$$

$$\left\{\left(\begin{array}{c}\left(\dfrac{x_{\tilde{B}_{\text{ĕ}}}(f)\, x_{\tilde{Z}_{\text{ţĕ}}}(f)}{\sqrt[3]{\vartheta + (1-\vartheta)\left(\left(x_{\tilde{B}_{\text{ĕ}}}(f)\right)^3 + \left(x_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3 - \left(\left(x_{\tilde{B}_{\text{ĕ}}}(f)\right)^3\left(x_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3\right)\right)}}\right), \\ \sqrt[3]{\dfrac{\left(y_{\tilde{B}_{\text{ĕ}}}(f)\right)^3 + \left(y_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3 - \left(\left(y_{\tilde{B}_{\text{ĕ}}}(f)\right)^3\left(y_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3\right) - (1-\vartheta)\left(\left(y_{\tilde{B}_{\text{ĕ}}}(f)\right)^3\left(y_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3\right)}{1-(1-\vartheta)\left(\left(y_{\tilde{B}_{\text{ĕ}}}(f)\right)^3\left(y_{\tilde{Z}_{\text{ţĕ}}}(f)\right)^3\right)}}\end{array}\right) \mid f \in F\right\} \tag{16}$$

herein, $\vartheta > 0$.

Step 2-3: To convert the FF fuzzy sets into crisp values, the score functions $\left(Sc(\mathbb{L}_{\text{ąĺ}})\right)$ is computed using Eq. (17). Thus, the crisp aggregated decision matrix $\left(Sc(\mathbb{L}_{\text{ąĺ}}) = [\mathbb{L}_{\text{ąĺ}}]_{\text{Ą}x\text{Ĺ}}\right)$ is derived.

$$Sc(\mathbb{L}_{\text{ąĺ}}) = \frac{1}{2}\left(1 + \left(x_{\widetilde{\mathbb{L}}_{\text{ąĺ}}}(f)\right)^3 - \left(y_{\widetilde{\mathbb{L}}_{\text{ąĺ}}}(f)\right)^3\right); \left(Sc(C_{\text{ąţ}}) \in [0,1]\right) \tag{17}$$

Step 2-4: In order to create the initial decision matrix including the overall criteria $\left(C = [C_{\text{ąţ}}]_{\text{Ą}x\text{Ţ}}\right)$, it is necessary to include the initial decision matrix for both the qualitative criteria $\left(\mathbb{L} = [\mathbb{L}_{\text{ąĺ}}]_{\text{Ą}x\text{Ĺ}}\right)$ and the quantitative criteria $\left(\mathbb{N} = [\mathbb{N}_{\text{ąň}}]_{\text{Ą}x\text{Ň}}\right)$.

Step 2-5: Normalization is accomplished using Eq. (18) for the cost and benefit criteria. Thus, a normalized decision matrix $\left(\kappa = [\kappa_{\text{ąţ}}]_{\text{Ą}x\text{Ţ}}\right)$ is obtained.

$$\kappa_{\text{ąţ}} = \begin{Bmatrix} \frac{C_{\text{ąţ}}}{C_{\text{ţ}}^{max}} \; for\ benefit\ criteria \\ \frac{C_{\text{ţ}}^{min}}{C_{\text{ąţ}}} \; for\ cost\ criteria \end{Bmatrix}; (\text{ą} = 1, \ldots, \text{Ą};\ \text{ţ} = 1, \ldots, \text{Ţ}) \tag{18}$$

Step 2-6: The decomposition is accomplished using Eq. (19). Thus, the decomposed decision matrix $\left(D = \left[D_{\text{ąţ}}\right]_{\text{Ą}x\text{Ţ}}\right)$ is obtained.

$$D_{\text{ąţ}} = max\left\{\left|\kappa_{\text{ąţ}} - \kappa_{\eta\text{ţ}}\right|\right\}; \left(\text{ą} = 1, \ldots, \text{Ą};\ \text{ţ} = 1, \ldots, \text{Ţ}; \eta = 1,2, \ldots\ \check{\text{N}}\right), (\eta \neq \text{ą}) \tag{19}$$

Step 2-7: Logarithmic decomposition is accomplished using Eq. (20). Thus, a logarithmic decomposed decision matrix $\left(\Upsilon = \left[\Upsilon_{\text{ţ}}\right]_{\text{Ţ}}\right)$ is obtained.

$$\Upsilon_{\text{ţ}} = ln\left(1 + \frac{\sum_{\text{ą}=1}^{\text{Ą}} D_{\text{ąţ}}}{\text{Ą}}\right); (\text{ą} = 1, \ldots, \text{Ą};\ \text{ţ} = 1, \ldots, \text{Ţ}) \tag{20}$$

Step 2-8: Using Eq. (21), the matrix of the weights $\left(\omega = \left[\omega_{\text{ţ}}\right]_{\text{Ţ}}\right)$ of the criteria is obtained.

$$\omega_{\text{ţ}} = \frac{\Upsilon_{\text{ţ}}}{\sum_{\text{ţ}=1}^{\text{Ţ}} \Upsilon_{\text{ţ}}} \tag{21}$$

Stage 3: *Final weighs of the criteria based on FF-CIMAS and FF-LODECI methods.*

Step 3-1: The criteria weights obtained by the subjective criteria weighting method FF-CIMAS method and the objective criteria weighting method FF- LODECI method are combined with Eq. (22) to obtain the final criteria weight matrix $\left(w = \left[w_{\text{ţ}}\right]_{\text{Ţ}}\right)$.

$$w_{\text{ţ}} = \lambda \text{ɰ}_{\text{ţ}} + (1 - \lambda)\omega_{\text{ţ}}; (\text{ţ} = 1, \ldots, \text{Ţ}) \tag{22}$$

Where λ is the parameter expressing the degree of importance of the subjective criterion weights and $\lambda \in [0,1]$.

Stage 4: *Ranking the alternatives based on FF-RADAR method* [20-21]

Step 4-1: The initial decision matrix $\left(C = \left[C_{\text{ąţ}}\right]_{\text{Ą}x\text{Ţ}}\right)$ is created as in Step 2-4.

Step 4-2: Using Eq. (23), the maximum proportion matrix is obtained separately for the benefit and cost criteria.

$$RADAR = \begin{cases} \alpha_{\text{ąţ}} = \dfrac{\frac{\max_{\text{ą}} C_{\text{ąţ}}}{C_{\text{ąţ}}}}{\frac{\max_{\text{ą}} C_{\text{ąţ}}}{C_{\text{ąţ}}} + \frac{C_{\text{ąţ}}}{\min_{\text{ą}} C_{\text{ąţ}}}}\ , for\ benefit\ criteria \\ \alpha_{\text{ąţ}} = \dfrac{\frac{C_{\text{ąţ}}}{\min_{\text{ą}} C_{\text{ąţ}}}}{\frac{\max_{\text{ą}} C_{\text{ąţ}}}{C_{\text{ąţ}}} + \frac{C_{\text{ąţ}}}{\min_{\text{ą}} C_{\text{ąţ}}}}\ , for\ cost\ criteria \end{cases} \tag{23}$$

Step 4-3: Using Eq. (24), the minimum proportion matrix is obtained separately for the benefit and cost criteria.

$$RADAR = \begin{cases} \beta_{\text{ĄŢ}} = \dfrac{\dfrac{c_{\text{ĄŢ}}}{\min\limits_{\text{Ą}} c_{\text{ĄŢ}}}}{\dfrac{\max\limits_{\text{Ą}} c_{\text{ĄŢ}}}{c_{\text{ĄŢ}}} + \dfrac{c_{\text{ĄŢ}}}{\min\limits_{\text{Ą}} c_{\text{ĄŢ}}}}\ , for\ benefit\ criteria \\ \beta_{\text{ĄŢ}} = \dfrac{\dfrac{\max\limits_{\text{Ą}} c_{\text{ĄŢ}}}{c_{\text{ĄŢ}}}}{\dfrac{\max\limits_{\text{Ą}} c_{\text{ĄŢ}}}{c_{\text{ĄŢ}}} + \dfrac{c_{\text{ĄŢ}}}{\min\limits_{\text{Ą}} c_{\text{ĄŢ}}}}\ , for\ cost\ criteria \end{cases} \tag{24}$$

Step 4-4: The values obtained in Step 4-2 and Step 4-3 are used in Eq. (25) to obtain the empty range matrix.

$$\theta_{\text{ąţ}} = \left|\alpha_{\text{ąţ}} - \beta_{\text{ąţ}}\right| \tag{25}$$

Step 4-5: The relative relationship matrix is obtained using Eq. (26).

$$I_{\text{ąţ}} = \frac{\alpha_{\text{ąţ}}}{\beta_{\text{ąţ}} + \theta_{\text{ąţ}}} \tag{26}$$

Step 4-6: The relative relationship matrix and the criteria weights are multiplied as in Eq. (27) to obtain the weighted relative relationship matrix.

$$\Pi_{\text{ąţ}} = I_{\text{ąţ}} * w_{\text{ţ}} \tag{27}$$

Step 4-7: Eq. (28) is used to calculate the aggregated ranking index of the alternatives. The alternative with the highest value among the obtained values becomes the best alternative.

$$\psi_{\text{ą}} = \frac{\min\left(\sum_{\text{ţ}=1}^{\text{Ţ}} \Pi_{\text{ąţ}}\right)}{\sum_{\text{ţ}=1}^{\text{Ţ}} \Pi_{\text{ąţ}}} \tag{28}$$

4. CASE STUDY

This case study was conducted to support the selection of a tractor for a green port in Türkiye. A panel consisting of experts specializing in green port operations was established to guide the evaluation process. A total of eight criteria (two quantitative and six qualitative) were identified to assess the alternatives. Additionally, five alternative tractor models suitable for green port operations were selected. This section presents detailed information regarding the experts' levels of expertise, descriptions of the evaluation criteria, and the specifications of the alternative tractors considered in the analysis.

4.1 Decision Model

4.1.1 Experts

A panel of ten experts working in green port operations in Türkiye was formed for this study. These experts possess varying levels of experience and domain-specific expertise. The composition of the expert panel based on their expertise levels is presented in Table 3. Through face-to-face interviews conducted with the expert group, the tractor alternatives were evaluated in accordance with the established criteria. This collaborative assessment ensured that both technical knowledge and practical experience were incorporated into the decision-making process.

Table 3 The expert group for assessing the green maritime transport performance criteria

Experts	Expertise Level	Professions
ϵ_1	Medium - M	Specialists in Green Port Operations-1
ϵ_2	Good - G	Specialists in Green Port Operations-2
ϵ_3	Good - G	Specialists in Green Port Operations-3
ϵ_4	Very Good - VG	Specialists in Green Port Operations-4
ϵ_5	Very Good - VG	Specialists in Green Port Operations-5
ϵ_6	Medium - M	Specialists in Green Port Operations-6
ϵ_7	Very Good - VG	Specialists in Green Port Operations-7
ϵ_8	Very Good - VG	Specialists in Green Port Operations-8
ϵ_9	Good - G	Specialists in Green Port Operations-9
ϵ_{10}	Very Good - VG	Specialists in Green Port Operations-10

4.1.2 Criteria Definition

In this study the definition of the criteria for the terminal tractor selection for green ports is based on several technical, economic, environmental and operational factors. The criteria are individually explained as follows:

Towing Capacity (ton) $(\eta_1 - \text{ŧ}_1)$: It is referred to as the maximum horizontal pulling force that can be safely and effectively exerted by the tractor to pull handling equipment or connected trailers. In full trailer models commonly used in ports, the load is completely supported by the trailer itself, and the terminal tractor merely provides the pulling force necessary to counteract friction as well as rolling resistance [14]. Towing capacity is a crucial performance indicator for ensuring that tractors can maneuver efficiently in tight spaces, maintain safe speeds under load, and endure the demanding, continuous operation cycles typical of terminal environments [35]. Additionally, having an adequate towing capacity is essential to maintaining smooth traffic flow and achieving high operational efficiency within the terminal [36].

Turning Radius (m) $(\eta_2 - \text{ŧ}_2)$: It is an important measure of performance that defines the smallest circular path a tractor-trailer combination can negotiate and has a direct impact on maneuverability within the limited areas typical of ports and terminals. According to Ma et al. terminal tractor design prefers narrow working spaces, frequent steering, and complex road surfaces, all needing a smaller turning radius for effective operation [14]. Reducing the turn radius allows terminal tractors to better fit into operational requirements where available space is narrow, such as trailer alignment, yard stacking, or vessel loading operations.

Energy Efficiency $(\text{ƀ}_1 - \text{ŧ}_3)$: It is a term that defines the capability to save energy consumption while maintaining the optimum working performance. As Brzeziński et al. pointed out, energy efficiency at terminals is crucial since handling vehicles like tractors can significantly affect the terminal daily energy requirement [37]. In addition, Martínez-Moya et al. demonstrate that yard tractors generate substantial amounts of CO_2 emissions and energy consumption in container terminals, underlining the need for more energy-efficient models and operational practices [38]. In this context, transitioning from dieselpowered to electric or hybrid has been identified as a key strategy to enhance energy efficiency while supporting environmental goals.

Emission Level $(ƚ_2 - ŧ_4)$: It refers to the quantity and mixture of pollutants released into the environment during operation, playing a critical role in contributing to air quality around port terminals. Terminal tractors have been identified as a major port-associated emission source, particularly CO_2 and NO_x, often accounting for over 25% of overall emissions at major terminals [4]. Emission rates vary depending on the fuel type: diesel tractors tend to have higher NO_x, and PM emissions compared to liquefied natural gas (LNG) or renewable natural gas-powered tractors [5]. In addition, electrification of terminal tractors has been proposed as a feasible alternative to lower life-cycle emissions significantly, especially in regions aiming for net-zero port operations. improvement in emission control technologies and cleaner energy sources are critical pathways to achieving sustainable and low-emission port operations [38].

Maintenance Cost $(ƚ_3 - ŧ_5)$: It refers to the total expenses incurred to ensure the continuous operational reliability, safety, and longevity of the terminal tractors, covering activities such as regular inspections, repairs, part replacements, and preventive maintenance. Maintenance cost is a significant part of total lifecycle expenses, especially when transitioning to electric terminal tractors, where although the upfront investment is high, the simplified mechanical systems can substantially reduce ongoing maintenance needs. Traditional terminal tractors driven by diesel engines, while more affordable to purchase initially, become more expensive in terms of maintenance costs because of such variables as engine deterioration, transmission overhaul, and greater component failure under port use [39]. Additionally, operational challenges such as tire damage, particularly in harsh terminal environments, contribute notably to the maintenance costs, necessitating systematic inspection and failure analysis programs.

Total Cost of Ownership (TCO) $(ƚ_4 - ŧ_6)$: It considers all the direct and indirect expenses of purchasing, operating, maintaining, energy consumption, and final disposal of the vehicle for its life cycle. Terminal tractor TCO analysis points out that while electric or fuel cell-based models cost more to buy than their diesel equivalents, they can reach the same cost after a few years due to the lower maintenance and fuel expenses [1]. According to Olivari et al., terminal tractor electrification is more economically viable when taking into consideration possible future advancements in battery technology and forecasted decreases in energy prices [11].

Ease of Use $(ƚ_5 - ŧ_7)$: It refers to the degree to which operators can efficiently, comfortably, and safely operate the control systems and interfaces of the vehicle during various cargo handling activities. In port environments, where frequent maneuvering and coupling/decoupling of trailers is required, an ergonomic and user-friendly tractor design is crucial in order to prevent operator fatigue and reduce operational errors [14]. Recent studies on dashboard and control interface design for electric terminal tractors emphasize that user-centered design approaches, such as employing familiar graphical elements and minimizing unnecessary complexity, significantly improve driver comfort and operational smoothness during the transition from diesel to electric models.

Port Infrastructure Suitability $(ƚ_6 - ŧ_8)$: It refers to the compatibility between the vehicle's operational requirements with the port environment's design and technical requirements. As Ma et al. have pointed out, terminal tractors must be designed for narrow working sites, complex road surfaces, frequent breaking, and long continuous working hours, so their design is highly coupled with the physical characteristics and operation flows of the terminal [14]. Moreover, Yang observes that the adoption of green and automated technologies in terminals requires a high degree of infrastructural adjustment, particularly about energy supply networks and layout planning optimization [40]. Infrastructure readiness also affects how well electric, or hybrid tractor adoption can be achieved, since charging infrastructure, turning radii, and trailer handling areas must be adapted to tractor design specifications.

4.1.3 Alternatives Definition

In the specific case study addressing the issue of the terminal tractor selection for green ports, the potential options are explained below:

Kalmar Ottawa (a_1): These terminal tractors have a high usage rate in terminal operations worldwide. The Kalmar Ottawa T2 model stands out with its compact chassis design, optimized field of view and fast maneuverability. The modular structure of the vehicle provides easy maintenance and low total cost of ownership [41].

Terberg YT (a_2): These series terminal tractors are durable and flexible tractors widely preferred in European and Asian markets. Models such as YT193 and YT220 offer high efficiency in narrow port areas thanks to their strong chassis structure and optimized turning circle. The vehicles are equipped with an adjustable fifth wheel structure that adapts to different trailer heights [42].

TICO Pro-Spotter (a_3): It has a high market share especially in domestic terminal and storage areas in the United States. The Pro-Spotter series is known for its spacious cabin design and durable powertrain systems that focus on operator comfort. The use of Volvo Penta electric powertrains in the latest generation models has increased the energy efficiency of the vehicles and reduced maintenance costs [43].

Capacity TJ Series (a_4): They are durable vehicles designed specifically for heavy-duty transportation and high-density terminal operations. Models such as the TJ5000 and TJ6500 offer a wide range of usage flexibility with both off-road and DOT (highway) compliant versions. The new generation models developed by Capacity Trucks feature high-lift capacity hydraulic fifth wheel systems and optimized chassis weight distribution [44].

The MAFI T 230e (a_5): It is specially designed for sustainable port operations as a fully electric terminal tractor. It maximizes energy efficiency thanks to its high-capacity lithium-ion batteries and regenerative braking system. MAFI has significantly improved operator ergonomics in the T 230e model by offering low chassis height and increased visibility [45].

4.1.4 Evaluating Tractor using the FF-Hamacher-CIMAS-LODECI-RADAR Hybrid Model

The tractor selection process based on expert evaluations was conducted by sequentially applying the steps of the FF-Hamacher-CIMAS-LODECI-RADAR hybrid method. The expert proficiency levels are presented in Table 4, while the experts' evaluation vectors for the criteria are provided in Table 5. The expert-based evaluation matrix of the tractor alternatives according to the criteria is shown in Table 6. As a result of the application, the criteria weight vector is presented in Table 7, and the tractor ranking vector is given in Table 8. According to the results, Towing Capacity was identified as the most significant criterion, and the MAFI T 230e was determined to be the highest-performing tractor alternative.

Table 4 The significant levels of the experts

Expert	Experience	FF Numbers		Score Functions	$\Psi_{ĕ}$
		$x_{\tilde{F}}(f)$	$y_{\tilde{F}}(f)$		
ϵ_1	Medium - M	0.42	0.52	0.47	0.0709
ϵ_2	Good - G	0.73	0.10	0.69	0.1054
ϵ_3	Good - G	0.73	0.10	0.69	0.1054
ϵ_4	Very Good - VG	0.82	0.50	0.71	0.1084
ϵ_5	Very Good - VG	0.82	0.50	0.71	0.1084
ϵ_6	Medium - M	0.42	0.52	0.47	0.0709
ϵ_7	Very Good - VG	0.82	0.50	0.71	0.1084
ϵ_8	Very Good - VG	0.82	0.50	0.71	0.1084
ϵ_9	Good - G	0.73	0.10	0.69	0.1054
ϵ_{10}	Very Good - VG	0.82	0.50	0.71	0.1084

Table 5 The criterion assessment matrix with LVs

Experts	$ƀ_1 - \eta_1$	$ƀ_2 - \eta_2$	$ƀ_3 - ƅ_1$	$ƀ_4 - ƅ_2$	$ƀ_5 - ƅ_3$	$ƀ_6 - ƅ_4$	$ƀ_7 - ƅ_5$	$ƀ_8 - ƅ_6$
ϵ_1	H	VH	VH	H	A	H	ExH	VH
ϵ_2	VH	VH	EH	AA	AA	H	EH	VH
ϵ_3	H	H	H	AA	H	H	EH	H
ϵ_4	AA	VH	H	H	H	AA	VH	H
ϵ_5	H	H	VH	H	A	H	ExH	H
ϵ_6	VH	H	VH	A	A	H	VH	VH
ϵ_7	H	VH	H	H	A	AA	VH	H
ϵ_8	H	H	VH	A	H	H	EH	VH
ϵ_9	AA	VH	VH	AA	AA	AA	ExH	H
ϵ_{10}	AA	VH	H	A	AA	AA	EH	AA

Table 6 The initial decision matrix with linguistic expressions

Experts	Alternatives	$ƀ_3 - ƅ_1$	$ƀ_4 - ƅ_2$	$ƀ_5 - ƅ_3$	$ƀ_6 - ƅ_4$	$ƀ_7 - ƅ_5$	$ƀ_8 - ƅ_6$
ϵ_1	a_1	VH	EH	AA	VH	AA	H
	a_2	EH	EH	VH	H	AA	H
	a_3	H	EH	H	EH	H	AA
	a_4	VH	EH	A	A	BA	A
	a_5	EH	ExH	H	VH	H	H
ϵ_2	a_1	VH	VH	H	EH	AA	H
	a_2	EH	VH	VH	VH	AA	EH
	a_3	H	VH	VH	VH	H	A
	a_4	VH	VH	BA	A	AA	AA
	a_5	EH	EH	AA	VH	H	VH
ϵ_3	a_1	VH	EH	AA	H	H	H
	a_2	EH	EH	H	H	VH	H
	a_3	H	EH	H	EH	H	AA
	a_4	H	EH	A	A	BA	AA

	a_5	VH	ExH	H	H	VH	VH
ϵ_4	a_1	EH	EH	VH	AA	H	EH
	a_2	EH	EH	H	H	H	VH
	a_3	VH	EH	H	VH	AA	AA
	a_4	H	EH	A	AA	AA	H
	a_5	EH	ExH	H	VH	H	VH
ϵ_5	a_1	EH	EH	VH	AA	VH	EH
	a_2	EH	EH	H	H	VH	VH
	a_3	VH	EH	H	VH	AA	AA
	a_4	H	EH	AA	H	H	H
	a_5	EH	ExH	VH	H	VH	H
ϵ_6	a_1	EH	H	VH	H	VH	VH
	a_2	EH	H	AA	H	VH	VH
	a_3	H	H	H	VH	AA	AA
	a_4	H	H	AA	H	H	H
	a_5	EH	VH	AA	VH	AA	H
ϵ_7	a_1	EH	EH	VH	VH	VH	VH
	a_2	VH	EH	H	VH	H	VH
	a_3	H	EH	VH	VH	H	H
	a_4	AA	EH	AA	H	H	H
	a_5	VH	ExH	VH	H	AA	H
ϵ_8	a_1	EH	VH	VH	VH	EH	VH
	a_2	EH	VH	VH	H	H	H
	a_3	VH	VH	VH	VH	H	H
	a_4	H	VH	H	H	H	VH
	a_5	EH	EH	A	VH	H	VH
ϵ_9	a_1	H	VH	H	EH	VH	EH
	a_2	H	VH	H	VH	AA	VH
	a_3	AA	VH	H	EH	AA	VH
	a_4	A	VH	AA	VH	AA	EH
	a_5	H	EH	VH	AA	A	EH
ϵ_{10}	a_1	EH	EH	H	VH	A	AA
	a_2	EH	EH	A	EH	A	VH
	a_3	VH	EH	VH	ExH	AA	A
	a_4	EH	EH	H	H	BA	A
	a_5	EH	ExH	H	EH	A	AA

Table 7 The final criteria weights

	$ƀ_1 - η_1$	$ƀ_2 - η_2$	$ƀ_3 - ɓ_1$	$ƀ_4 - ɓ_2$	$ƀ_5 - ɓ_3$	$ƀ_6 - ɓ_4$	$ƀ_7 - ɓ_5$	$ƀ_8 - ɓ_6$
$w_ţ$	0.1549	0.0857	0.1070	0.1156	0.1297	0.1433	0.1196	0.1443
Rank	1	8	7	6	4	3	5	2

Table 8 The aggregated ranking index matrix

	Kalmar Ottawa (a_1)	Terberg YT (a_2)	TICO Pro-Spotter (a_3)	Capacity TJ Series (a_4)	The MAFI T 230e (a_5)
$\psi_{ą}$	0.9600	0.9940	0.8920	0.9390	1.0000
Rank	3^{rd}	2^{nd}	5^{th}	4^{th}	1^{st}

5. Results

In this study, a novel hybrid decision-making methodology (FF-Hamacher-CIMAS-LODECI-RADAR) was proposed and implemented to identify the most suitable tractor among various cargo handling equipment alternatives for green port operations. The methodology was applied to a real-life case involving a port currently operating in Türkiye. The decision-making model involved ten expert decision-makers, eight evaluation criteria, and five different tractor alternatives.

As a result of the application of the hybrid method, three primary outcomes were obtained:

Determination of Criterion Importance Levels: Through the integration of the FF-Hamacher-CIMAS-LODECI methodology, the weights of the evaluation criteria were calculated by combining both subjective (expert opinions) and objective (data-driven) perspectives. The weights of the criteria as follows: "*Towing Capacity (ton)* $(ŧ_1)$ $(w_1 = 0.1549)$ > *Port Infrastructure Suitability* $(ŧ_8)$ $(w_8 = 0.1443)$ > *Total Cost of Ownership (TCO)* $(ŧ_6)$ $(w_6 = 0.1433)$ > *Maintenance Cost* $(ŧ_5)$ $(w_5 = 0.1297)$ > *Ease of Use* $(ŧ_7)(w_7 = 0.1196)$ > *Emission Level* $(ŧ_4)$ $(w_4 = 0.1156)$ > *Energy Efficiency* $(ŧ_3)$ $(w_3 = 0.1070)$ > *Turning Radius (m)* $(ŧ_2)$ $(w_2 = 0.0857)$*"* According to the final importance ranking of criteria, Towing Capacity (ton) was identified as the most influential factor in the decision-making process, while Turning Radius (m) was ranked as the least important. This outcome can be attributed to the specific characteristics of the port under consideration; namely, the port area offers sufficient spatial allowance, thus diminishing the criticality of turning radius in operational scenarios. Conversely, towing capacity directly reflects the operational power and efficiency of the tractors, indicating its fundamental role in sustainable cargo handling processes.

Ranking of Tractor Alternatives: Using the RADAR method, tractor alternatives were evaluated and ranked according to their performance across the determined criteria. The ranking of the tractors as follows: "The *MAFI T 230e* (a_5) $(\psi_5 = 1.000)$ > *Terberg YT* (a_2) $(\psi_5 = 0.994)$ > *Kalmar Ottawa* (a_1) $(\psi_1 = 0.960)$ > *Capacity TJ Series* (a_4) $(\psi_4 = 0.939)$ > *TICO Pro-Spotter* (a_3) $(\psi_5 = 0.892)$" The final ranking revealed that the MAFI T 230e tractor emerged as the most suitable alternative for green port implementation. This model was followed by other alternatives in descending order of performance, consistent with the aggregated performance scores derived from the decision model.

Validation of Methodological Applicability: The successful application of the FF-Hamacher-CIMAS-LODECI-RADAR hybrid methodology demonstrated its capability to effectively support multi-criteria decision-making in the selection of eco-efficient cargo handling equipment. The method enabled a transparent, structured, and rigorous evaluation process by integrating fuzzy logic with subjective and objective weight derivation techniques, as well as a robust ranking algorithm.

In conclusion, the findings of this study underscore the practical relevance and decision-making robustness of the proposed hybrid methodology. By guiding the selection of the most appropriate tractor aligned with green port objectives, the method provides a replicable framework for other ports seeking to enhance their sustainability performance through informed equipment procurement strategies.

5.1 Sensitivity Analysis for Robustness

To validate the reliability and robustness of the tractor selection results obtained through the FF-Hamacher-CIMAS-LODECI-RADAR hybrid methodology for green port operations, a series of sensitivity analysis scenarios were designed. The primary objective of these scenarios was to observe the stability of the results under varying conditions and to assess the resilience of the proposed method against changes in methodological parameters. Within this scope, three distinct sensitivity scenarios were developed and analyzed.

Scenario 1 - *Impact of Varying Weighting Techniques*: This scenario was designed to examine how changes in the relative contribution of the FF-Hamacher-CIMAS and FF-Hamacher-LODECI weighting techniques would influence the final ranking of tractor alternatives. A parameter denoted as λ was introduced to represent the contribution coefficient of the FF-Hamacher-CIMAS method in the overall weighting process. By incrementally adjusting the λ parameter from 0 to 1, the model simulated varying levels of influence from the respective methods.

The findings, illustrated in Fig. 2 (tractor performance scores) and Fig. 3 (ranking orders), reveal that when the λ coefficient approaches zero (indicating minimal contribution from the CIMAS method) the highest-ranking tractor shifts to *Terberg YT*. Conversely, as the influence of CIMAS increases ($\lambda \rightarrow 1$), The *MAFI T 230e* regains its position as the top performer. The analysis concludes that an λ value of 0.5 yields the most balanced outcome, suggesting that equal contributions from both weighting methods enhance the objectivity and consistency of the decision-making process.

Scenario 2 - *Influence of Qualitative vs. Quantitative Criteria*: The second scenario was developed to test the performance of the hybrid method when only qualitative or quantitative criteria were used independently in the decision model. This aimed to evaluate the hybrid methodology's capability to integrate both types of data simultaneously, a key advantage in complex multi-criteria decision environments.

According to the results, depicted in Fig. 4 (performance scores) and Fig. 5 (alternative rankings), if only qualitative criteria were considered, *Kalmar Ottawa* would have been selected as the best alternative. Conversely, if only quantitative criteria were employed, *Terberg YT* would have emerged as the top choice. However, when both types of criteria were integrated using the proposed hybrid method, The *MAFI T 230e* was consistently identified as the most suitable tractor. These findings emphasize the methodological limitation of relying solely on one data type and demonstrate how the hybrid approach effectively mitigates potential decision-making biases, ensuring a more holistic and accurate evaluation.

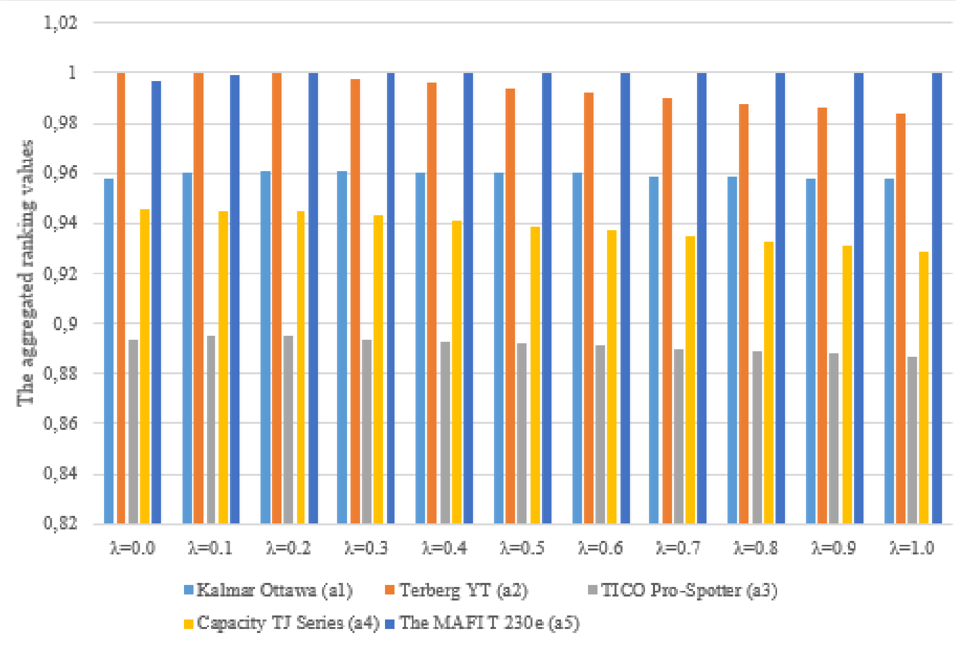

Fig. 2 Results according to first sensitivity scenario

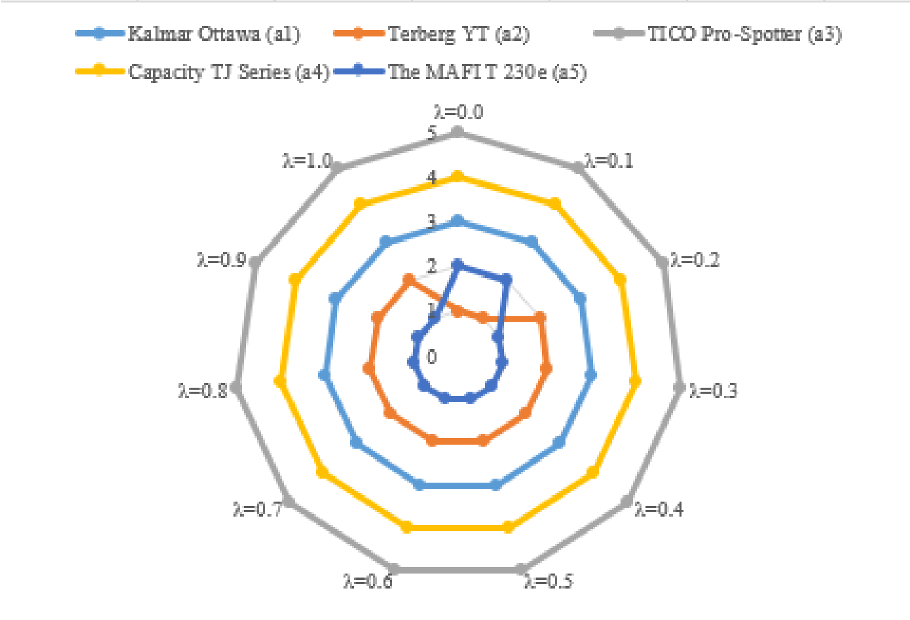

Fig. 3 Ranks according to first sensitivity scenario

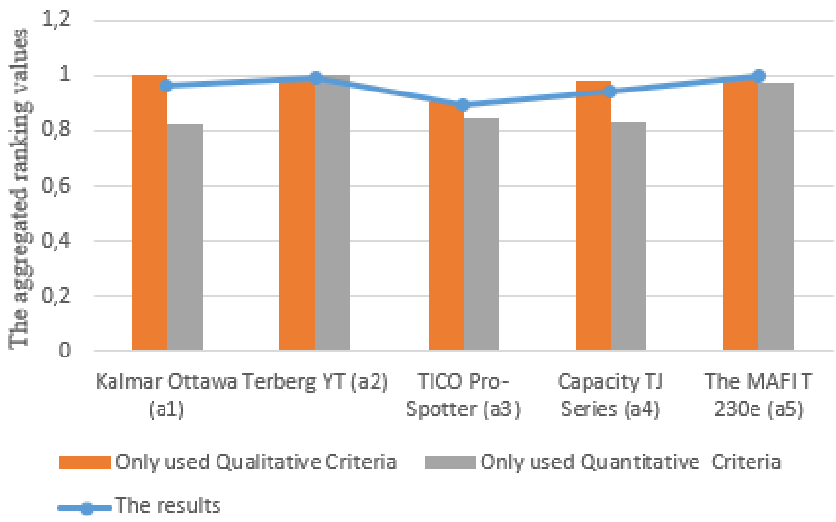

Fig. 4 Results according to the second sensitivity scenario

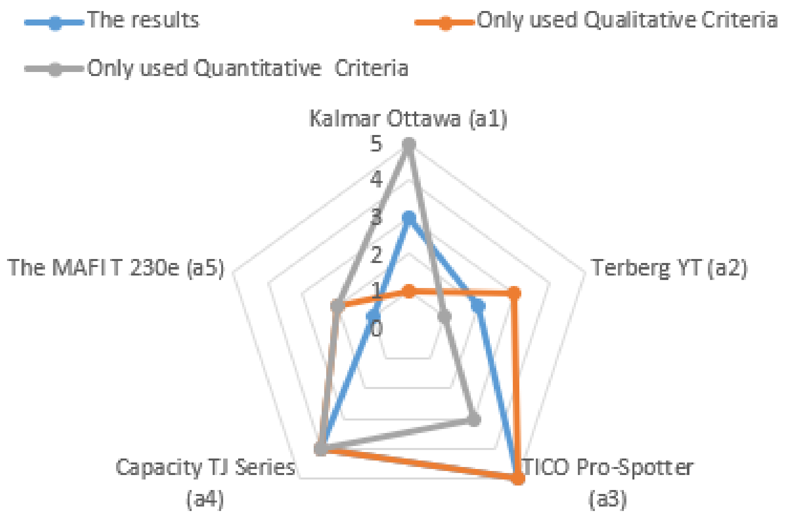

Fig. 5 Ranks according to second sensitivity scenario

Scenario 3 - *Evaluation of Tractor Suitability under Alternative Conditions*: The third sensitivity scenario aimed to verify the consistency of the selection of The *MAFI T 230e* as the top-performing tractor by testing its dominance across various sub-scenarios. In each sub-scenario, the lowest-performing tractor (based on the original ranking) was systematically removed from the model, and the evaluation process was repeated to identify the new top performer.

As shown in Fig. 6 and summarized in Table 9, The *MAFI T 230e* remained the top-ranked tractor across all sub-scenarios, thereby confirming its robust performance and suitability for green port operations under varying configurations. This consistency reinforces the accuracy and stability of the proposed hybrid methodology in identifying optimal alternatives.

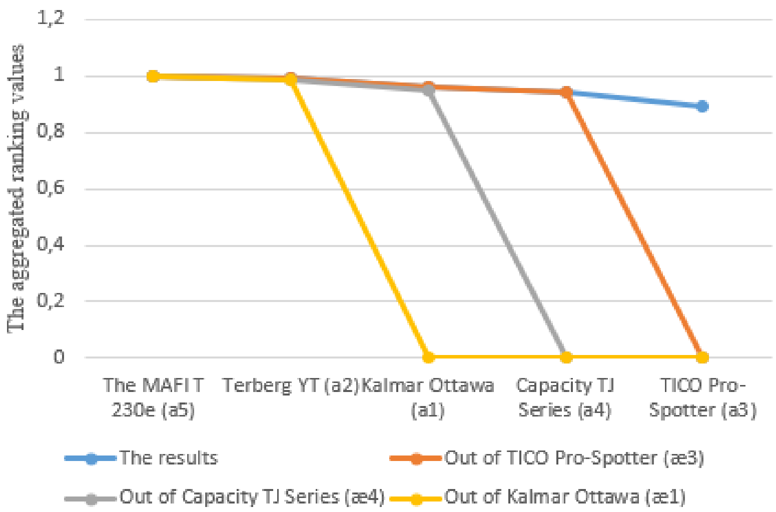

Fig. 6 Results according to third sensitivity scenario

Table 9 The ranks according to third sensitivity scenario

SAS-3 scenarios	Ranking	Best Performance
Result	$a_5 > a_2 > a_1 > a_4 > a_3$	The MAFI T 230e
SAS-3a: Removed a_3	$a_5 > a_2 > a_1 > a_4$	The MAFI T 230e
SAS-3b: Removed a_4	$a_5 > a_2 > a_1$	The MAFI T 230e
SAS-3c: Removed a_1	$a_5 > a_2$	The MAFI T 230e

In conclusion, the outcomes of all three sensitivity scenarios confirm the robustness, reliability, and adaptability of the FF-Hamacher-CIMAS-LODECI-RADAR hybrid methodology. The consistent identification of the same optimal tractor under different analytical conditions validates the method as an effective decision-support tool for equipment selection in sustainable port management. Therefore, the proposed hybrid methodology can be confidently considered as an ideal approach for supporting strategic decision-making in the context of green port development.

5.2 Comparative Analysis for Consistency

To evaluate the effectiveness and reliability of the proposed FF-Hamacher-CIMAS-LODECI-RADAR hybrid method for tractor selection in green port operations, a comparative analysis was conducted using alternative ranking methodologies widely recognized in the literature. Specifically, fifteen alternative multi-criteria decision-making

(MCDM) methods were applied to the same dataset to derive tractor performance scores and corresponding rankings. These methods include RADAR II [46], RAWEC [47,48], CORASO [49], ALWAS [50], AROMAN [51], RATGOS [52], MABAC [53-55], MARCOS [56], RAM [57], SAW, WASPAS [58], ARLON [59], OPARA [60], WEDBA [61], and COCOSO [62-64].

The ranking outcomes derived from these methods are presented in Fig. 7. Upon examination of the results, it was found that the top-performing tractor (*The MAFI T 230e*) and the lowest-performing tractor (*TICO Pro-Spotter*) remained consistent across all fifteen methods, thereby confirming the robustness of these alternatives within varying methodological contexts.

However, minor deviations were observed in the middle ranks. Specifically, four of the methods (MABAC, MARCOS, WEDBA, and COCOSO) produced a slight change in the order between the third-ranked tractor (*Kalmar Ottawa*) and the fourth-ranked tractor (*Capacity TJ Series*) when compared to the proposed hybrid method. This variation highlights the sensitivity of certain methods to slight differences in performance criteria weighting and aggregation procedures.

Furthermore, a correlation analysis was conducted to examine the statistical relationship between the performance scores of tractors as determined by the proposed hybrid method and each of the alternative methods. The correlation coefficients are presented in Table 10. The results reveal that the FF-Hamacher-CIMAS-LODECI-RADAR hybrid method demonstrates a very high level of correlation with all alternative methods, indicating strong consistency and alignment in decision outcomes.

In summary, the findings from this comparative analysis support the validity and reliability of the proposed hybrid methodology. Its ability to produce consistent rankings across a wide range of established MCDM methods reinforces its suitability as a robust decision-support tool for selecting environmentally suitable tractors in green port operations.

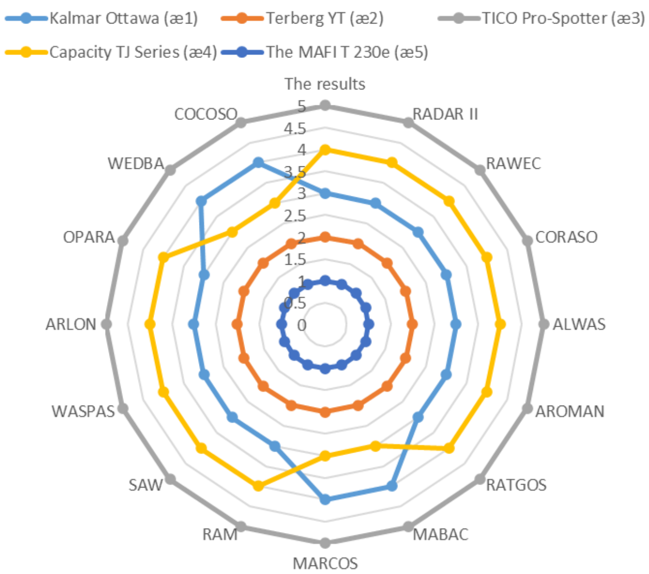

Fig. 7 Ranks according to comparative analysis

Table 10 The correlation analysis results

Methods	The results	RADAR II	RAWEC	CORASO	ALWAS	AROMAN	RATGOS	MABAC	MARCOS	RAM	SAW	WASPAS	ARLON	OPARA	WEDBA	COCOSO
The results	1.00	0.92	0.98	0.98	0.95	1.00	0.99	0.98	0.98	0.99	0.98	0.98	0.99	0.97	0.94	0.97
RADAR II		1.00	0.87	0.87	0.99	0.95	0.89	0.89	0.87	0.90	0.87	0.87	0.94	0.87	0.80	0.88
RAWEC			1.00	1.00	0.89	0.97	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	0.99	1.00
CORASO				1.00	0.89	0.97	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	0.99	1.00
ALWAS					1.00	0.98	0.91	0.91	0.89	0.92	0.89	0.90	0.95	0.89	0.82	0.89
AROMAN						1.00	0.98	0.97	0.97	0.98	0.97	0.97	0.99	0.96	0.92	0.96
RATGOS							1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.98	1.00
MABAC								1.00	1.00	1.00	1.00	1.00	0.99	1.00	0.98	1.00
MARCOS									1.00	1.00	1.00	1.00	0.98	1.00	0.99	1.00
RAM										1.00	1.00	1.00	0.99	1.00	0.98	0.99
SAW											1.00	1.00	0.98	1.00	0.99	1.00
WASPAS												1.00	0.99	1.00	0.99	1.00
ARLON													1.00	0.98	0.95	0.99
OPARA														1.00	0.99	1.00
WEDBA															1.00	0.99
COCOSO																1.00

6. Conclusion

This study developed a decision support system aimed at selecting the most suitable tractor for green port operations. The proposed system integrates the FF-Hamacher-CIMAS-LODECI-RADAR hybrid method, which effectively combines subjective and objective criteria weighting through fuzzy Hamacher operations and utilizes the RADAR technique for ranking alternatives. The novelty of this approach lies in the simultaneous inclusion of both qualitative and quantitative criteria within a unified decision-making framework, enabling a comprehensive evaluation of alternative tractors tailored to the specific requirements of green ports.

The applicability of the hybrid method was demonstrated through a case study involving a green port in Türkiye, where a panel of ten experts evaluated five tractor types across eight criteria, including both technical and environmental factors. The findings identified The MAFI T 230e as the optimal tractor choice, with towing capacity emerging as the most significant criterion and turning radius as the least influential, justified by the expansive operational area of the port. Sensitivity analyses further confirmed the robustness and reliability of the model, while comparative assessments with fifteen alternative methods showed strong consistency and high correlation, validating the effectiveness of the proposed system.

Overall, this research contributes a novel, reliable, and practical decision support tool for green port management, facilitating informed and balanced equipment selection that aligns with sustainability goals. The results offer valuable insights for port authorities and industry stakeholders, supporting the advancement of environmentally conscious operations. Moreover, the robustness of the proposed hybrid method can be further reinforced through comparative analyses involving newly developed techniques [65] and alternative comparative frameworks [66]. Future research may also enhance the model's applicability by adapting it to diverse operational contexts and integrating additional evaluation criteria, thereby improving the effectiveness of decision-making processes in sustainable port logistics.

REFERENCES

1. Gilleon, S., Penev, M., Hunter, C., 2022, *Powertrain performance and total cost of ownership analysis for class 8 yard tractors and refuse trucks* (No. NREL/TP-5400-83968), National Renewable Energy Laboratory (NREL), Golden, CO (United States), https://doi.org/10.2172/1899989.
2. Sogut, M. Z., Erdoğan, O. 2022, *An investigation on a holistic framework of green port transition based on energy and environmental sustainability*, Ocean Engineering, 266, 112671.
3. Karagkouni, K., Boile, M., 2024, *Classification of green practices implemented in ports: The application of green technologies, tools, and strategies*, Journal of Marine Science and Engineering, 12(4), 571.
4. Li, C., Dixit, P., Welch, B., et al., 2021, *Yard tractors: Their path to zero emissions*, Transportation Research Part D: Transport and Environment, 98, 102972.
5. Tang, T., Zhu, H., Ma, T., Hao, P., Durbin, T. D., Johnson, K. C., Karavalakis, G., 2024, *A comparison between the gaseous and particulate emissions from diesel and natural gas yard tractors*, Emission Control Science and Technology, 10(2), pp. 162-174.
6. Okşaş, O., 2023, *Carbon emission strategies for container handling equipment using the activity-based method: A case study of Ambarlı container port in Turkiye*, Marine Policy, 149, 105480.
7. Foretich, A., Zaimes, G. G., Hawkins, T. R., Newes, E., 2021, *Challenges and opportunities for alternative fuels in the maritime sector*, Maritime Transport Research, 2, 100033.
8. Ashrafi, M., Lister, J., Gillen, D., 2022, *Toward a harmonization of sustainability criteria for alternative marine fuels*, Maritime Transport Research, 3, 100052.
9. Tadić, D., Lukić, J., Komatina, N., Marinković, D., Pamučar, D., 2025, *A Fuzzy Decision-Making Approach to Electric Vehicle Evaluation and Ranking*, Tehnički Vjesnik, 32(3), pp. 1066-1075.
10. Pirhadi, M., Krasowsky, T. S., Gatt, G., Quiros, D. C., 2024, *Criteria pollutant and greenhouse gas emissions from cargo handling equipment operating at the Ports of Los Angeles and Long Beach*, Science of the Total Environment, 927, 172084.
11. Olivari, E., Gurrì, S., Caballini, C., Carotta, T., Chiara, B. D., 2024, *Ports go green: a cost-energy analysis applied to a case study on evaluating the electrification of yard tractors*, The Open Transportation Journal, 18(1), e26671212308027.
12. Lombardi, S., Di Ilio, G., Tribioli, L., Jannelli, E., 2023, *Optimal design of an adaptive energy management strategy for a fuel cell tractor operating in ports*, Applied Energy, 352, 121917.
13. Hu, X., Guo, J., Zhang, Y., 2019, *Optimal strategies for the yard truck scheduling in container terminal with the consideration of container clusters*, Computers Industrial Engineering, 137, 106083.
14. Ma, Q., Wang, B., Dong, S., Li, H., Gu, X., Yu, C., Wang, H., 2024, *Port Tractors and Trailers*, in: Tao, D., Yan, Y., Dong, D., Zhang, D. (Eds.), *Handbook of Port Machinery*, Singapore, Springer Nature Singapore, pp. 847-915.
15. Senapati, T., Yager, R. R., 2020, *Fermatean fuzzy sets*, Journal of ambient intelligence and humanized computing, 11, pp. 663-674.
16. Radovanović, M., Božanić, D., Tešić, D., Puška, A., Hezam, I. M., Jana, C., 2023, *Application of hybrid DIBR-FUCOM-LMAW-Bonferroni-grey-EDAS model in multicriteria decision-making*, Facta Universitatis, Series: Mechanical Engineering, 21(3), pp. 387-403.
17. Hadi, A., Khan, W., Khan, A., 2021, *A novel approach to MADM problems using fermatean fuzzy hamacher aggregation operators*, International Journal of Intelligent Systems, 36(7), pp. 3464-3499.
18. Kara, K., Yalçın, G. C., Çetinkaya, A., Simic, V., Pamucar, D., 2024, *A single-valued neutrosophic CIMAS-CRITIC-RBNAR decision support model for the financial performance analysis: A study of technology companies*, Socio-Economic Planning Sciences, 92, 101851.
19. Pala, O., 2024, *Assessment of the social progress on european union by logarithmic decomposition of criteria importance*, Expert Systems with Applications, 238, 121846.

20. Komatina, N., Marinković, D., Tadić, D., Pamučar, D., 2025, *Advancing PFMEA decision-making: FRADAR based prioritization of failure modes using AP, RPN, and multi-attribute assessment in the automotive industry*, Tehnički Glasnik, 19(3), pp. 442-451.
21. Komatina, N., Marinkovic, D., Babič, M., 2026, *Fundamental Characteristics and Applicability of the RADAR Method: Proof of Ranking Consistency*, Spectrum of Operational Research, 3(1) 63-80.
22. Sornn-Friese, H., Poulsen, R. T., Nowinska, A. U., de Langen, P., 2021, *What drives ports around the world to adopt air emissions abatement measures?*, Transportation Research Part D: Transport and Environment, 90, 102644.
23. Mahmud, K. K., Chowdhury, M. M. H., Shaheen, M. M. A., 2024, *Green port management practices for sustainable port operations: a multi method study of Asian ports*, Maritime Policy & Management, 51(8), pp. 1902-1937.
24. Parhamfar, M., Sadeghkhani, I., Adeli, A. M., 2023, *Towards the application of renewable energy technologies in green ports: Technical and economic perspectives*, IET Renewable Power Generation, 17(12), pp. 3120-3132.
25. Peng, Y., Liu, H., Li, X., Huang, J., Wang, W., 2020, *Machine learning method for energy consumption prediction of ships in port considering green ports*, Journal of Cleaner Production, 264, 121564.
26. Zhen, L., Zhuge, D., Murong, L., Yan, R., Wang, S., 2019, *Operation management of green ports and shipping networks: overview and research opportunities*, Frontiers of Engineering Management, 6(2), pp. 152-162.
27. Zhang, Z., Song, C., Zhang, J., et al., 2024, *Digitalization and innovation in green ports: A review of current issues, contributions and the way forward in promoting sustainable ports and maritime logistics*, Science of the Total Environment, 912, 169075.
28. Zhou, Y., Zhang, Y., Ma, D., et al., 2020, *Port-related emissions, environmental impacts and their implication on green traffic policy in Shanghai*, Sustainability, 12(10), 4162.
29. Densberger, N. L., Bachkar, K., 2022, *Towards accelerating the adoption of zero emissions cargo handling technologies in California ports: lessons learned from the case of the ports of Los Angeles and long beach*, Journal of Cleaner Production, 347, 131255.
30. Wei, D., Giuliano, G., 2025, *Estimating the economic impacts of cargo handling equipment electrification: A case study of the San Pedro Bay ports*, Research in Transportation Business & Management, 59, 101281.
31. Cai, L., Li, W., Li, H., Zhou, B., He, L., Guo, W., Yang, Z., 2024, *Incorporation of energy-consumption optimization into multi-objective and robust port multi-equipment integrated scheduling*, Transportation Research Part C: Emerging Technologies, 166, 104755.
32. Liu, W., Zhu, X., Wang, L., Zhang, Q., Tan, K. C., 2023, *Integrated scheduling of yard and rail container handling equipment and internal trucks in a multimodal port*, IEEE Transactions on Intelligent Transportation Systems, 25(3), pp. 2987-3008.
33. Stoilova, S. D., Martinov, S. V., 2019, *Choosing the container handling equipment in a rail-road intermodal terminal through multi-criteria methods*, In IOP Conference Series: Materials Science and Engineering, IOP Publishing. https://doi.org/10.1088/1757-899X/664/1/012032.
34. Shahzadi, G., Luqman, A., Ali Al-Shamiri, M. M., 2022, *The extended MOORA method based on fermatean fuzzy information*, Mathematical problems in engineering, 2022(1), 7595872.
35. Petering, M. E., 2011, *Decision support for yard capacity, fleet composition, truck substitutability, and scalability issues at seaport container terminals*, Transportation Research Part E: Logistics and Transportation Review, 47(1), pp. 85-103.
36. Abourraja, M. N., Kringos, N., Meijer, S., 2022, *Exploiting simulation model potential in investigating handling capacity of Ro-Ro terminals: The case study of Norvik seaport*, Simulation Modelling Practice and Theory, 117, 102513.
37. Brzeziński, M., Pyza, D., Archutowska, J., Budzik, M., 2024, *Method of estimating energy consumption for intermodal terminal loading system design*, Energies, 17(24), 6409.
38. Martínez-Moya, J., Vazquez-Paja, B., Maldonado, J. A. G., 2019, *Energy efficiency and CO2 emissions of port container terminal equipment: Evidence from the Port of Valencia*, Energy Policy, 131, pp. 312-319.
39. Huang, W. C., Chu, C. Y., 2004, *A selection model for in-terminal container handling systems*, Journal of Marine Science and Technology, 12(3), 4.
40. Yang, Y. C., 2015, *Determinants of container terminal operation from a green port perspective*, International Journal of Shipping and Transport Logistics, 7(3), pp. 319-346.
41. https://www.kalmarottawa.com (last access: 29.06.2025)
42. https://www.terberggroup.com (last access: 29.06.2025)
43. https://ticotractors.com (last access: 29.06.2025)
44. https://capacitytrucks.com (last access: 29.06.2025)
45. https://www.mafi.de (last access: 29.06.2025)

46. Komatina, N., 2025, *A Novel BWM-RADAR approach for multi-attribute selection of equipment in the automotive industry*, Spectrum of Mechanical Engineering and Operational Research, 2(1), pp. 104-120.
47. Puška, A., Štilić, A., Pamučar, D., Božanić, D., Nedeljković, M., 2024, *Introducing a novel multi-criteria ranking of alternatives with weights of criterion (RAWEC) model,* MethodsX, 12, 102628.
48. Özekenci, E. K., 2025, *A Multi-Criteria Framework for Economic Decision Support in Urban Sustainability: Comparative Insights from European Cities*, International Journal of Economic Sciences, 14(1), 162-181.
49. Puška, A., Nedeljković, M., Božanić, D., Štilić, A., Muhsen, Y. R., 2024, *Evaluation of agricultural drones based on the COmpromise Ranking from Alternative SOlutions (CORASO) methodology*, Engineering Review, 44, pp. 77-90.
50. Pamucar, D., Ecer, F., Gligorić, Z., Gligorić, M., Deveci, M., 2023, *A novel WENSLO and ALWAS multicriteria methodology and its application to green growth performance evaluation*, IEEE Transactions on Engineering Management, 71, pp. 9510-9525.
51. Bošković, S., Švadlenka, L., Jovčić, S., Dobrodolac, M., Simić, V., Bacanin, N., 2023, *An alternative ranking order method accounting for two-step normalization (AROMAN)—A case study of the electric vehicle selection problem,* IEEE Access, 11, pp. 39496-39507.
52. Dinçer, H., Eti, S., Yüksel, S., Özdemir, S., Yílmaz, A. E., Ergün, E., 2023, *Integrating data mining and fuzzy decision-making techniques for analyzing the key minimizing factors of carbon emissions*, Journal of intelligent & fuzzy systems, 45(5), pp. 7317-7333.
53. Pamučar, D., Ćirović, G., 2015, *The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC)*, Expert systems with applications, 42(6), pp. 3016-3028.
54. Tadić, D., Komatina, N., 2025, *A hybrid interval type-2 fuzzy DEMATEL-MABAC approach for strategic failure management in automotive manufacturing*, Journal of Engineering Management and Systems Engineering (JEMSE), 4(1), pp. 21-38.
55. Božanić, D., Borota, M., Štilić, A., Puška, A., Milić, A., 2024, *Fuzzy DIBR II-MABAC model for flood prevention: A case study of the river Veliki Rzav*, Journal of Decision Analytics and Intelligent Computing, 4(1), 285-298.
56. Stević, Ž., Pamučar, D., Puška, A., Chatterjee, P., 2020, *Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS)*, Computers & industrial engineering, 140, 106231.
57. Sotoudeh-Anvari, A., 2023, *Root Assessment Method (RAM): A novel multi-criteria decision making method and its applications in sustainability challenges*, Journal of Cleaner Production, 423, 138695.
58. Chakraborty, S., Zavadskas, E. K., 2014, *Applications of WASPAS method in manufacturing decision making*, Informatica, 25(1), pp. 1-20.
59. Kara, K., Yalçın, G. C., Simic, V., Baysal, Z., Pamucar, D., 2024, *The alternative ranking using two-step logarithmic normalization method for benchmarking the supply chain performance of countries*, Socio-Economic Planning Sciences, 92, 101822.
60. Mehdi, K. G., Abdolghani, R., Maghsoud, A., Zavadskas, E. K., Antuchevičienė, J., 2024, *Multi-Criteria personnel evaluation and selection using an objective pairwise adjusted ratio analysis (OPARA)*, Economic computation and economic cybernetics studies and research., 58(2), pp. 23-45.
61. Rao, R. V., Singh, D., 2012, *Weighted Euclidean distance based approach as a multiple attribute decision making method for plant or facility layout design selection*, International Journal of Industrial Engineering Computations, 3(3), pp. 365-382.
62. Yazdani, M., Zarate, P., Kazimieras Zavadskas, E., Turskis, Z., 2019, *A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems,* Management decision, 57(9), pp. 2501-2519.
63. Dhal, P. R., Choudhury, B. B., Sahoo, S. K., 2024, *Evaluating motor choices for a smart wheelchair prototype using an integrated TODIM-CoCoSo approach with MEREC weighting*, Engineering Review, 44(4) pp. 22-44.
64. Saha, A., Chatterjee, P., 2025, *A Fermatean Fuzzy Decision-Making Model for Manufacturing Outsourcing Vendor Selection: An Improved Combined Compromise Solution Method*, Spectrum of Mechanical Engineering and Operational Research, 2(1), 231-247.
65. Zaman, M. M. K., Rodzi, Z. M., Andu, Y., Shafie, N. A., Sanusi, Z. M., Ghazali, A. W., Mahyideen, J. M., 2025, *Adaptive Utility Ranking Algorithm for Evaluating Blockchain-Enabled Microfinance in Emerging-A New MCDM Perspective*. International Journal of Economic Sciences, 14(1), 123-146.
66. Więckowski, J., Sałabun, W., 2025, *Comparative sensitivity analysis in composite material selection: Evaluating OAT and COMSAM methods in multi-criteria decision-making*. Spectrum of Mechanical Engineering and Operational Research, 2(1), pp. 1-12.