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A Fermatean Fuzzy MCDM Framework for Green Port Transformation and Heavy-Duty Forklift Selection

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Abstract: The rapid growth of global trade has heightened the importance of efficient container handling, environmentally responsible operations, and high-performing equipment selection in sustaining the competitiveness of modern supply chains. Container Freight Stations (CFS) serve as critical operational hubs where loading, unloading, inspection, and temporary storage activities are conducted, thereby requiring equipment capable of safely and efficiently handling heavy-tonnage cargo while aligning with green port transformation goals. Forklifts, which constitute one of the core equipment groups in CFS yards, differ significantly in terms of lifting capacity, power systems, maneuverability, hydraulic performance, ergonomics, and environmental impact, transforming forklift selection into a complex, multi-dimensional decision problem shaped by both technical and Environmental, Social, and Governance (ESG)-oriented considerations. Incorrect equipment choices may lead to operational downtime, energy inefficiency, equipment failures, and occupational safety risks, particularly in operations involving loads exceeding 25 tons. To address these challenges, this study proposes a hybrid decision-making framework that integrates expert-driven fuzzy assessments with sustainability-based evaluation using the FF-Hamacher-MEREC-ARLON methodology. In the first stage, expert weights and criterion importance values were calculated through the FF-MEREC approach, while alternative forklifts were ranked using the FF-ARLON method in the second stage. Two sensitivity analysis scenarios were applied: one by modifying the tradeoff ratio within ARLON and the other by sequentially removing each criterion. In both scenarios, the fourth alternative consistently emerged as the most suitable option. Furthermore, comparative analyses using eight established MCDM techniques; ALWAS, AROMAN, ARTASI, MABAC, MARCOS, RAM, SAW, and WASPAS; demonstrated complete agreement with the proposed model, confirming the fourth alternative as the top-ranked choice. The findings highlight the robustness, reliability, and sustainability alignment of the proposed framework for high-stakes heavy-duty equipment selection in port-based logistics operations.

Keywords: Container Freight Stations; Fermatean fuzzy sets; Hamacher aggregation operator; MEREC; ARLON

1 Introduction

With the increase in global trade volume, the efficiency of container transportation and port operations, as well as the diversity offered at the service level, have become among the most critical factors determining the competitiveness of supply chains. In this context, Container Freight Stations (CFS), where container loading, unloading, inspection, and temporary storage processes are carried out, play a strategic role in the continuity of terminal operations [1]. Today, port operators have made improving environmental performance, energy efficiency, and carbon footprint among their core objectives in line with green port policies [2]. This transformation process directly impacts the selection of operational equipment for CFS yards.

Handling heavy tonnage cargo in CFS yards requires a high level of equipment and technology for operational safety, efficiency, and sustainability [3]. The ability to handle heavy tonnage cargo is directly determined by the technical and functional specifications of the forklifts used in the field. Forklifts are among the essential equipment for cargo handling in CFS yards. However, each forklift model; they vary in terms of lifting capacity, energy type, maneuverability, hydraulic system, and ergonomic design. This diversity transforms the selection process from an evaluation limited to technical parameters to a multi-dimensional decision-making problem centered on sustainability.

In this context, the appropriate selection of forklifts to be used in the field depends not only on physical capacity but also on Environmental, Social, and Governance (ESG)-based criteria. In CFS operations, particularly where loads exceeding 25 tons are handled, the wrong forklift selection can lead to negative consequences such as equipment failures, operational delays, fuel waste, and occupational safety risks. Therefore, forklift selection is not only a technical investment decision; it has also become an integral component of sustainable operational strategies aligned with ports' green transformation policies.

2 Literature Review

ESG has become a vital component in establishing policies for sustainable development in the maritime logistics and port sectors. ESG frameworks provide ports with a multidimensional structure in terms of improving environmental performance, strengthening social responsibility, and enhancing transparency and accountability in governance. Investigations have shown that investor expectations are increasingly focused not only on financial returns but also on conformance with ESG practices that shape strategic decisions and affect resilience within supply chains [4].

Current studies of ESG performance in ports indicate that there is a need to incorporate environmental impacts, energy use, waste management, social responsibility practices, and quality of governance into integrated assessment systems. Quantitative ESG performance evaluation models have been developed that enable comparison among international ports based on structured sustainability benchmarking and informed responsible investment decisions. Such models emphasize the ability of ESG indicators to capture the environmental and social performance profile of ports as a structured basis for evaluating sustainability maturity across different port systems [5].

Literature also explores the impact of ESG practices on port resilience. System dynamics models indicate that ESG-driven strategies enhance the ability of ports to bounce back from disruptions, reduce risks, and maintain operational continuity. Evidence exists that improved environmental performance, along with enhanced social sustainability measures and amplified governance mechanisms, combine to realize better levels of port resilience and stable patterns of long-term development [6].

Studies on ESG in port management show that ports benefit from clear frameworks that support their sustainability efforts. Such frameworks incorporate policies, programs, processes, and partnerships to support the systematic ESG integration approach. In fact, research done in the Brazilian context has demonstrated how collaborative guides to sustainability enable ports to implement ESG principles with international alignment while responding to local regulatory and operational peculiarities, creating an organizational culture favorable to long-term sustainable development [7].

Empirical research on Chinese ports also uncovers the role of ESG indicators in the evaluation of sustainable port development. These studies apply analytical techniques like DEA and CRITIC weighting to analyze environmental efficiency, carbon emission performance, energy use, social responsibility, and governance quality. The results prove that ESG metrics provide a full-scale and comparable analysis of port performance and permit the identification of critical strengths and weaknesses at the environmental, social, and governance levels [8, 9]. This kind of empirical ESG-based evaluation represents an important tool for guiding ports in pursuing sustainable strategic objectives.

Other studies examine organizational and operational issues in ESG practice adoption by ports. These works have identified financial constraints, institutional capacity, regulatory compliance needs, and stakeholder expectations as important factors that shape ESG adoption processes. As the port sector continues to evolve, effective strategic management of ESG factors is increasingly recognized as central to determining sustainable growth, good governance, and organizational legitimacy. The broader ESG literature within the maritime sector stresses the interconnectedness of environmental sustainability, social responsibility, and corporate governance. Review documents indicate that ESG applications influence corporate behavior, stakeholder engagement, reporting quality, and value creation over the longer term. Additionally, it has been shown that ESG practices influence industry-wide standards regarding transparency, risk management, and ethical governance-things that confirm the potential for transformation in ESG applications within the maritime domain [10].

Lastly, a review of the broader literature indicates that while ESG occupies a central position in port operations, there is a noticeable scarcity of studies that explicitly integrate ESG considerations into critical technical decision-making processes, such as the selection of heavy-duty equipment. This indicates that technical decisions like heavy-duty forklift selection should be re-evaluated through an ESG perspective, and that addressing this gap through advanced methodological frameworks would offer a significant contribution to the literature.

3 Methodology

3.1 Preliminaries of Fermatean Fuzzy (FF) Sets

Definition 1. FF sets, which are based on fuzzy logic and defined over fuzzy numbers, can be formally described within a universe X as follows: In such a set, $\mu_{\tilde{A}}(x)$ and $\vartheta_{\tilde{A}}(x)$ represent the membership and non-membership degrees, respectively, while $\pi_{\tilde{A}}(x)$ denotes the indeterminacy degree calculated as $\pi_{\tilde{A}}(x)=\sqrt[3]{1-(\mu_{\tilde{A}}(x))^3-(\vartheta_{\tilde{A}}(x))^3}$. These values satisfy the condition $0 \leq (\mu_{\tilde{A}}(x))^3+(\vartheta_{\tilde{A}}(x))^3 \leq 1$ for all $x \in X$ [11].

Definition 2. Let $\tilde{A}_1=\{\langle x, \mu_{\tilde{A}_1}(x), \vartheta_{\tilde{A}_1}(x) \mid x \in X\rangle\}$ and $\tilde{A}_2=\{\langle x, \mu_{\tilde{A}_2}(x), \vartheta_{\tilde{A}_2}(x) \mid x \in X\rangle\}$ be two FF sets. The corresponding definitions of these operations are provided below [12]:

(i) $\tilde{A}_1 \oplus \tilde{A}_2=\left\{\left(\sqrt[3]{(\mu_{\tilde{A}_1}(x))^3+(\mu_{\tilde{A}_2}(x))^3-(\mu_{\tilde{A}_1}(x))^3(\mu_{\tilde{A}_2}(x))^3}, (\vartheta_{\tilde{A}_1}(x)\vartheta_{\tilde{A}_2}(x))\right) \mid x \in X\right\}$,

(ii) $\tilde{A}_1 \otimes \tilde{A}_2=\left\{\left((\mu_{\tilde{A}_1}(x)\mu_{\tilde{A}_2}(x)), \sqrt[3]{(\vartheta_{\tilde{A}_1}(x))^3+(\vartheta_{\tilde{A}_2}(x))^3-(\vartheta_{\tilde{A}_1}(x))^3(\vartheta_{\tilde{A}_2}(x))^3}\right) \mid x \in X\right\}$,

(iii) $\eta\tilde{A}_1=\left\{\left(\sqrt[3]{1-\left(1-(\mu_{\tilde{A}_1}(x))^3\right)^\eta}, (\vartheta_{\tilde{A}_1}(x))^\eta\right) \mid x \in X\right\}$ for $\eta>0$,

(iv) $\tilde{A}_1^\eta=\left\{\left((\mu_{\tilde{A}_1}(x))^\eta \cdot \sqrt[3]{1-\left(1-(\vartheta_{\tilde{A}_1}(x))^3\right)^\eta}\right) \mid x \in X\right\}$ for $\eta>0$.

Definition 3. A score function is utilized to convert FF sets into numerical values. If the score functions of two FF sets yield identical results, an accuracy function is then employed to further distinguish between them. Consider two FF sets, $\tilde{A}_1=\{\langle x, \mu_{\tilde{A}_1}(x), \vartheta_{\tilde{A}_1}(x) \mid x \in X\rangle\}$ and $\tilde{A}_2=\{\langle x, \mu_{\tilde{A}_2}(x), \vartheta_{\tilde{A}_2}(x) \mid x \in X\rangle\}$. The score function $\left(\mathrm{S}\left(\tilde{A}_1\right)\right)$ for the first FF set $\tilde{A}$ is computed as shown in Eq. (1), whereas its accuracy function $\left(\mathrm{Ac}\left(\tilde{A}_1\right)\right)$ is determined according to Eq. (2) [13].

$$S\left(\tilde{A}_1\right)=\frac{\left(1+(\mu_{\tilde{A}_1}(x))^3-(\vartheta_{\tilde{A}_1}(x))^3\right)}{2} \tag{1}$$

$$Ac\left(\tilde{A}_1\right)=(\mu_{\tilde{A}_1}(x))^3+(\vartheta_{\tilde{A}_1}(x))^3 \tag{2}$$

3.2 Hamacher t-norm and t-conorm Based Aggregation Operator for FF Sets

Definition 4. The computations of the Hamacher t-norm (TN) and t-conorm (TCN) are carried out according to Eq. (3) and Eq. (4), respectively [12]:

$$\mathrm{TN}(\alpha,\beta)=\frac{\alpha\beta}{\tau+(1-\tau)(\alpha+\beta-\alpha\beta)} \tag{3}$$

$$\mathrm{TCN}(\alpha,\beta)=\frac{\alpha+\beta-\alpha\beta-(1-\tau)\alpha\beta}{1-(1-\tau)\alpha\beta} \tag{4}$$

herein, $\alpha, \beta \in [0,1]$ and $\tau>0$.

Definition 5. Consider a group of FF sets identified as $\tilde{A}_r=\{\langle x, \mu_{\tilde{A}_r}(x), \vartheta_{\tilde{A}_r}(x) \mid x \in X\rangle\}$. The FFHWA aggregation operator is computed by performing Eq. (5) [12]:

$$\begin{gathered}\mathrm{FFHWA}(\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_r, \ldots, \tilde{A}_R)=\bigoplus_{r=1}^{R}\eta_r\tilde{A}_r= \\ \left(\sqrt[3]{\frac{\prod_{r=1}^{R}\left(1+(\tau-1)(\mu_{\tilde{A}_r}(x))^3\right)^{\eta_r}-\prod_{r=1}^{R}\left(1-(\mu_{\tilde{A}_r}(x))^3\right)^{\eta_r}}{\prod_{r=1}^{R}\left(1+(\tau-1)(\mu_{\tilde{A}_r}(x))^3\right)^{\eta_r}+(\tau-1)\prod_{r=1}^{R}\left(1-(\mu_{\tilde{A}_r}(x))^3\right)^{\eta_r}}},\right. \\ \left.\frac{\sqrt[3]{\tau}\prod_{r=1}^{R}\left(\vartheta_{\tilde{A}_r}(x)\right)^{\eta_r}}{\sqrt[3]{\prod_{r=1}^{R}\left(1+(\tau-1)\left(1-(\vartheta_{\tilde{A}_r}(x))^3\right)\right)^{\eta_r}+(\tau-1)\prod_{r=1}^{R}\left(\vartheta_{\tilde{A}_r}(x)\right)^{3\eta_r}}}\right)\end{gathered} \tag{5}$$

The corresponding vector $\eta_l = (\eta_1, \eta_2, \ldots, \eta_r, \ldots, \eta_R)$ represents the weight vector relation with $\tilde{A}_r$ $(r = 1, 2, \ldots, R)$. Also, $\eta_r > 0$ and $\sum_{r=1}^{R} \eta_r = 1$ and $\tau > 0$. The proof was done by Hadi et al. [12].

3.3 The Novel FF-Hamacher-MEREC-ARLON Hybrid Method

In this study, which aims to support the sustainable and high-performance selection of forklifts used in CFS operations, a hybrid decision-making framework integrating ESG-based evaluation and expert-driven assessments is proposed. The model combines FF-Hamacher-MEREC-ARLON hybrid method approach to address uncertainty in expert judgments and the multidimensional nature of heavy-duty equipment selection. Within this framework, technical performance indicators, environmental impacts, operator safety, and governance-related factors are simultaneously evaluated through structured expert inputs and fuzzy aggregation techniques. In this way, the forklift selection process is conducted by incorporating both sustainability-oriented criteria and robust computational decision tools, enabling ports to make more reliable, objective, and green-transformation-aligned investment decisions.

In this study, ESG-based assessments are considered quantitative assessments, while expert-focused assessments are considered qualitative assessments. In this framework, the constituents of the decision model are characterized as experts $(E = \{E_1, E_2, \ldots, E_k, \ldots, E_K\}$ $(k = 1, 2, \ldots, K))$, quantitative criteria $(U = \{U_1, U_2, \ldots, U_b, \ldots, U_B\}$ $(b = 1, 2, \ldots, B))$, qualitative criteria $(V = \{V_1, V_2, \ldots, V_d, \ldots, V_D\}$ $(d = 1, 2, \ldots, D))$, overall criteria $(C = \{C_1, C_2, \ldots, C_j, \ldots, C_n\}$ $(j = 1, 2, \ldots, n)$; $(B + D = C))$, and alternatives $(A = \{A_1, A_2, \ldots, A_i, \ldots, A_m\}$ $(i = 1, 2, \ldots, m))$.

The study was conducted in two stages. In the first stage, expert weights were identified and criterion weights were calculated using the FF-MEREC method. In the second stage, alternatives were ranked using the FF-ARLON method. The application steps of the FF-Hamacher-MEREC-ARLON hybrid method are outlined as follows:

• **Stage 1** FF-MEREC method [14]:

Step 1: Table 1 is used to calculate the expert weights. After converting the linguistically expressed expert levels into fuzzy numbers, the score function values are obtained using Eq. (6). The expert weights are calculated by normalizing them using Eq. (7).

Table 1. Expertise levels [15]

Expertise Levels	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)
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)

Table 2. Linguistic terms for evaluating criteria/alternatives [15]

Linguistic Terms	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)

$$S(E_k) = \frac{\left(1 + \left(\mu_{\tilde{E}_k}(x)\right)^3 - \left(\vartheta_{\tilde{E}_k}(x)\right)^3\right)}{2} \tag{6}$$

$$w_k = \frac{S(E_k)}{\sum_{k=1}^{K} S(E_k)} \tag{7}$$

Step 2: Experts use Table 2 to linguistically evaluate each alternative according to each qualitative criterion. Linguistic expressions are converted into fuzzy numbers.

Step 3: The assessments made by the experts are aggregated using Eq. (8).

$$w_k \bigotimes \tilde{X}_{idk} = \left(\sqrt[3]{\frac{\prod_{k=1}^{K} \left(1 + (\tau - 1)(\mu_{\tilde{X}_{idk}}(x))^3\right)^{w_k} - \prod_{k=1}^{K} \left(1 - (\mu_{\tilde{X}_{idk}}(x))^3\right)^{w_k}}{\prod_{k=1}^{K} \left(1 + (\tau - 1)(\mu_{\tilde{X}_{idk}}(x))^3\right)^{w_k} + (\tau - 1) \prod_{k=1}^{K} \left(1 - (\mu_{\tilde{X}_{idk}}(x))^3\right)^{w_k}}}, \frac{\sqrt[3]{\tau} \prod_{k=1}^{K} \left(\vartheta_{\tilde{X}_{idk}}(x)\right)^{w_k}}{\sqrt[3]{\prod_{k=1}^{K} \left(1 + (\tau - 1)\left(1 - (\vartheta_{\tilde{X}_{idk}}(x))^3\right)\right)^{w_k} + (\tau - 1) \prod_{k=1}^{K} \left(\vartheta_{\tilde{X}_{idk}}(x)\right)^{3w_k}}} \right) \tag{8}$$

Step 4: The aggregated expert assessments are defuzzified using Eq. (9).

$$S\left(\tilde{X}_{id}\right) = \frac{\left(1 + \left(\mu \tilde{X}_{id}(x)\right)^3 - \left(\vartheta_{\tilde{X}_{id}}(x)\right)^3\right)}{2} \tag{9}$$

Step 5: The initial decision matrix is created by combining the defuzzified expert assessments with quantitative criteria.

Step 6: The initial decision matrix is normalized using Eq. (10).

$$N_{ij} = \begin{cases} \frac{\min(X_{ij})}{X_{ij}}, j \in C^+ \\ \frac{X_{ij}}{\max(X_{ii})}, j \in C^- \end{cases} ; (i = 1, \ldots, m; j = 1, \ldots, n) \tag{10}$$

Step 7: The overall performance matrix for each alternative is calculated with Eq. (11).

$$O_j = \ln\left(1 + \left(\frac{1}{n} \sum_{j=1}^{n} |\ln(N_{ij})|\right)\right) \tag{11}$$

Step 8: The partial performance matrix for each alternative is calculated with Eq. (12).

$$P_{ij} = \ln\left(1 + \left(\frac{1}{n} \sum_{z, z \neq j}^{n} |\ln(N_{ij})|\right)\right) ; (z, j = 1, \ldots, n) \tag{12}$$

Step 9: The total absolute deviation matrix for each criterion is calculated with Eq. (13).

$$T_j = \sum_{i=1}^{m} |P_{ij} - O_j| \tag{13}$$

Step 10: The criteria weight matrix based on the FF-MEREC method is calculated with Eq. (14).

$$\mathfrak{w}_j = \frac{T_j}{\sum_{j=1}^{n} T_j} \tag{14}$$

• **Stage 2:** Ranking of the alternatives based on FF-ARLON method [16].

Step 1: The elements of the aggregated decision matrix obtained as a result of qualitative criterion evaluations are multiplied by 100, and quantitative criteria are combined to obtain the initial decision matrix.

Step 2: The obtained decision matrix is subjected to two different logarithmic normalization processes using Eq. (15) and (16).

$$L_{ij}^{1}=\begin{cases} L_{ij}^{1(+)}=\dfrac{\ln(X_{ij})}{\ln\left(\prod\limits_{i=1}^{m}X_{ij}\right)}, j\in C^{+} \\ L_{ij}^{1(-)}=\dfrac{1-\frac{\ln(X_{ij})}{\ln\left(\prod\limits_{i=1}^{m}X_{ij}\right)}}{R-1}, j\in C^{-} \end{cases} \tag{15}$$

$$L_{ij}^{2}=\begin{cases} L_{ij}^{2(+)}=\dfrac{\log_2(X_{ij})}{\sum\limits_{i=1}^{m}(\log_2(X_{ij}))}, j\in C^{+} \\ L_{ij}^{2(-)}=1-\dfrac{\log_2(X_{ij})}{\sum\limits_{i=1}^{m}(\log_2(X_{ij}))}, j\in C^{-} \end{cases} \tag{16}$$

Step 3: Normalized decision matrices are combined using the Heron mean method with Eq. (17).

$$H_{ij}=\left((1-\gamma)\sqrt{\left(L_{ij}^{1}\right)\left(L_{ij}^{2}\right)}+(\gamma)\frac{\left(L_{ij}^{1}\right)+\left(L_{ij}^{2}\right)}{2}\right) \tag{17}$$

herein, $\gamma\in[0,1]$ indicates the tradeoff ratio.

Step 4: The resulting aggregated decision matrix is weighted using the criterion weights and Eq. (18).

$$\mathbb{W}_{ij}=\mathfrak{w}_{j}H_{ij} \tag{18}$$

Step 5: The weighted values are calculated separately for benefit criteria and cost criteria using Eq. (19) and (20).

$$\mathcal{C}_{i}^{-}=\sum_{j}^{n}\mathbb{W}_{ij};\ \text{for } j\in C^{-} \tag{19}$$

$$\mathcal{B}_{i}^{+}=\sum_{j}^{n}\mathbb{W}_{ij};\ \text{for } j\in C^{+} \tag{20}$$

Step 6: The performance matrix of the alternatives is determined using Eq. (21).

$$\mathrm{G}_{i}=\left(\left(\mathcal{B}_{i}^{+}\right)^{\varkappa}+\left(\mathcal{C}_{i}^{-}\right)^{(1-\varkappa)}\right) \tag{21}$$

The $\varkappa\in[0,1]$ parameter is obtained by dividing the total number of benefit criteria by the total number of criteria.

Step 7: To rank the alternatives according to the ARLON method, Eq. (22) is used as the final step. This yields the final ranking:

$$\mathbb{R}_{i}=\frac{\mathrm{G}_{i}-\min\mathrm{G}_{i}}{\max\mathrm{G}_{i}-\min\mathrm{G}_{i}} \tag{22}$$

4 Application

4.1 Evaluation Criteria and Healthcare Company Alternatives for the Analysis Financial Performance

In this study, 10 criteria grouped under 4 main headings are identified as critical for forklift selection in CFS operations. These criteria were defined through a focused literature review and expert insights, reflecting both operational requirements and the sustainability priorities of green port initiatives.

4.1.1 Decision model

(1) Expert Group

Based on the scope and objectives of this study, a group of ten experts involved in port and logistics operations was consulted to aid the assessment process. These experts were selected due to their professional experience and familiarity with CFS activities, heavy-duty equipment management, and sustainability practices within green port environments. Their contributions assisted in identifying and prioritizing the key technical and ESG-related criteria, as well as supporting the evaluation of forklift alternatives in line with the operational and environmental requirements of modern port systems.

(2) Criteria

In this study, the definition of the criteria for ESG-based forklift selection in CFS operations is grounded in a combination of environmental, social, governance, and technical performance factors. These criteria were identified to reflect both the operational requirements of heavy-duty cargo handling and the sustainability priorities of green port practices.

Emission & Fuel Consumption (C_1): Evaluates the environmental burden and operational energy performance of forklifts by considering their power source and the actual energy they consume during lifting and maneuvering tasks. Studies comparing diesel and LPG forklifts show that engine type and operating environment significantly influence overall emission intensity and energy demand, with heavier loads and more dynamic driving patterns leading to higher outputs [17].

Energy Efficiency (C_2): Reflects the capability of a forklift's powertrain and hydraulic subsystems to minimize energy losses and optimize performance during lifting, maneuvering, and braking cycles. Research shows that modern electric and hybrid forklifts increasingly rely on mechatronic innovations—such as regenerative braking, advanced motor control, and optimized energy storage—to recover kinetic and potential energy and reduce overall energy demand [18].

Ergonomics (C_3): Design characteristics enhancing operator comfort, visibility, vibration, and noise reduction. Research on human-truck interaction shows that ergonomic shortcomings can increase musculoskeletal load, discomfort, and operational fatigue, directly affecting both performance and safety outcomes [19].

Safety Systems (C_4): Safety systems refer to the integration of hardware and control technologies designed to ensure the stability, collision avoidance, and safe trajectory tracking of forklifts during operation [20].

Attachment Flexibility (C_5): Attachment flexibility refers to the capability of a forklift to safely integrate and operate with different interchangeable equipment (such as clamps, reel handlers, or side-shifters) while maintaining stability, rated capacity, and safety compliance [21].

Telematics & Traceability (C_6): Telematics and traceability involve the integration of IoT sensors, blockchain, and digital platforms to ensure real-time visibility, integrity of data, and traceable documentation of equipment operations and lifecycle performance. Within supply chains, the systems record the movement, usage, and condition of assets, enabling the sharing of transparent and tamper-proof data among stakeholders and, further, ensuring accountability for meeting sustainability goals [22].

Load Capacity (ton) (C_7): Represents the nominal lifting capacity of the forklift in tonnes. As highlighted in the literature on advanced forklift selection, load-carrying capacity is one of the primary technical determinants influencing the suitability of a forklift for heavy-duty or height-dependent material-handling tasks, directly shaping both operational performance and safety outcomes [23].

Motor Power (kW) (C_8): The rated output power of the engine or electric drive motor. Empirical studies demonstrate that forklifts with higher engine power exhibit improved dynamic performance, particularly during loaded driving, lifting operations, and work cycles requiring rapid acceleration or sustained torque delivery [18].

Overall Width (mm) (C_9): Represents the total lateral dimension of the forklift chassis and serves as a key geometric parameter affecting stability, maneuverability, and load-handling dynamics. Dynamic modeling studies indicate that a forklift's structural dimensions—including its chassis width—directly shape the distribution of forces and oscillations experienced during load lifting, influencing both lateral stability and the behavior of critical components such as the mast, chains, and hydraulic cylinders [24].

Turning Radius (m) (C_{10}): Represents the minimum circular space a forklift requires to change direction, and it is widely recognized as one of the key geometric parameters influencing maneuverability, operational safety, and layout efficiency. Research on forklift dynamics identifies the turning radius determining a vehicle's ability to navigate confined industrial or warehouse aisles, with conventional rear-wheel-steered forklifts exhibiting larger turning paths and increased risks related to stability and overturning during sharp directional changes [25].

(3) Heavy-Duty Forklift Alternatives

In the specific case study addressing the selection of forklifts for CFS operations, the potential equipment alternatives are explained below.

Hyundai 250D-9V (A_1): A 25-ton Stage V diesel forklift equipped with a Cummins L9 engine, load-sensing hydraulics, ZF automatic transmission, and Hi-MATE telematics, offering balanced performance, safety, and ergonomics [26].

Hyundai 300D-9VC (A_2): A 30-ton heavy-duty diesel model using the same Cummins L9 power unit, designed for higher-load stability with efficient hydraulics and advanced operator comfort features [27].

Kalmar DCG250 (A_3): A 25-ton diesel forklift powered by a Volvo D8/Cummins 6.7 engine, featuring Eco Mode fuel savings, EGO ergonomic cabin, and optional Insight telematics for efficient, low-emission operation [28].

Kalmar ECG250 (A_4): A 25-ton fully electric lithium-ion forklift with regenerative braking, thermal management, zero local emissions, and built-in Insight connectivity for superior ESG performance [29].

Hyster H40XD-12 (A_5): A 40-ton high-capacity diesel forklift using a Cummins QSM11 engine and Spicer TE-30 transmission, providing exceptional durability and attachment versatility but higher fuel consumption [30].

The steps of the FF-Hamacher-MEREC-ARLON hybrid method were sequentially applied to selection of heavy-duty forklifts:

• **Stage 1** FF-MEREC method

Table 3. The significant levels of the experts

Expert	Experience	FF Sets		$S(E_k)$	w_k
		$\mu_{\tilde{E}_k}(x)$	$\vartheta_{\tilde{E}_k}(x)$		
E_1	G	0.73	0.10	0.69	0.1132
E_2	VG	0.82	0.50	0.71	0.1163
E_3	M	0.42	0.52	0.47	0.0761
E_4	M	0.42	0.52	0.47	0.0761
E_5	G	0.73	0.10	0.69	0.1132
E_6	P	0.36	0.41	0.49	0.0797
E_7	VG	0.82	0.50	0.71	0.1163
E_8	VG	0.82	0.50	0.71	0.1163
E_9	P	0.36	0.41	0.49	0.0797
E_{10}	G	0.73	0.10	0.69	0.1132

Table 4. The initial decision matrices with LVs

Expert	Alternative	C_1	C_2	C_3	C_4	C_5	C_6
	A_1	EL	BA	AA	H	VH	ExH
	A_2	BA	VH	VH	H	ExH	H
E_1	A_3	H	H	AA	H	VH	ExH
	A_4	ExH	ExH	ExH	ExH	ExH	ExH
	A_5	EL	BA	BA	H	ExH	BA
	A_1	VL	A	H	AA	EH	EH
	A_2	BA	H	EH	H	EH	AA
E_2	A_3	H	H	H	VH	H	EH
	A_4	EH	EH	ExH	EH	EH	ExH
	A_5	EL	A	A	H	EH	A
	A_1	VL	A	H	H	VH	EH
	A_2	BA	H	H	H	H	H
E_3	A_3	A	H	VH	H	VH	ExH
	A_4	EH	EH	ExH	ExH	ExH	ExH
	A_5	EL	BA	BA	H	ExH	BA
	A_1	EL	BA	AA	H	VH	ExH
	A_2	BA	AA	H	H	AA	H
E_4	A_3	EH	AA	AA	VH	VH	EH
	A_4	EH	EH	VH	ExH	EH	ExH
	A_5	VL	A	BA	H	VH	BA
	A_1	EL	BA	AA	AA	EH	EH
	A_2	BA	AA	H	H	EH	AA
E_5	A_3	VH	AA	VH	VH	VH	EH
	A_4	EH	EH	ExH	ExH	EH	ExH
	A_5	EL	BA	BA	H	VH	BA
	A_1	BA	H	H	H	EH	VH
	A_2	A	AA	H	H	EH	AA
E_6	A_3	A	AA	AA	VH	H	EH
	A_4	EH	EH	ExH	ExH	EH	ExH
	A_5	EL	AA	A	VH	VH	BA
	A_1	EL	BA	AA	H	EH	VH
	A_2	BA	VH	VH	H	ExH	H
E_7	A_3	VH	H	VH	H	VH	ExH
	A_4	EH	EH	ExH	ExH	ExH	ExH
	A_5	EL	BA	BA	H	ExH	BA
	A_1	VL	A	A	H	VH	EH
	A_2	BA	VH	VH	VH	EH	H
E_8	A_3	EH	H	H	VH	H	EH
	A_4	EH	EH	EH	ExH	ExH	ExH
	A_5	VL	BA	A	VH	EH	BA
	A_1	EL	BA	BA	A	AA	H
	A_2	A	H	AA	VH	A	A
E_9	A_3	H	VH	VH	H	VH	ExH
	A_4	ExH	ExH	ExH	ExH	ExH	ExH
	A_5	EL	BA	BA	H	ExH	BA
	A_1	VL	A	AA	AA	VH	A
	A_2	BA	BA	BA	H	AA	A
E_{10}	A_3	H	VH	H	VH	ExH	EH
	A_4	ExH	EH	EH	EH	ExH	ExH
	A_5	L	L	A	H	EH	A

Expert information and expert weights are shown in Table 3. The linguistic expressions of the alternatives evaluated by experts according to qualitative criteria are presented in Table 4, and their fuzzy number equivalents are presented in Table 5. The combined decision matrix is shown in Table 6. The initial decision matrix to be used in the MEREC method is shown in Table 7. The normalized decision matrix is shown in Table 8. The overall performance values of the alternatives are shown in Table 9. The partial performance values of the alternatives are shown in Table 10. The total of absolute deviations and criterion weights are shown in Table 11.

Table 5. The initial decision matrices with FF sets

Experts	**Alternatives**	C_1		C_2		C_3		C_4		C_5		C_6	
	A_1	0.35	0.43	0.42	0.30	0.50	0.62	0.55	0.38	0.60	0.18	0.83	0.42
	A_2	0.42	0.30	0.60	0.18	0.60	0.18	0.55	0.38	0.83	0.42	0.55	0.38
E_1	A_3	0.55	0.38	0.55	0.38	0.50	0.62	0.55	0.38	0.60	0.18	0.83	0.42
	A_4	0.83	0.42	0.83	0.42	0.83	0.42	0.83	0.42	0.83	0.42	0.83	0.42
	A_5	0.35	0.43	0.42	0.30	0.42	0.30	0.55	0.38	0.83	0.42	0.42	0.30
	A_1	0.36	0.56	0.47	0.21	0.55	0.38	0.50	0.62	0.72	0.50	0.72	0.50
	A_2	0.42	0.30	0.55	0.38	0.72	0.50	0.55	0.38	0.72	0.50	0.50	0.62
E_2	A_3	0.55	0.38	0.55	0.38	0.55	0.38	0.60	0.18	0.55	0.38	0.72	0.50
	A_4	0.72	0.50	0.72	0.50	0.83	0.42	0.72	0.50	0.72	0.50	0.83	0.42
	A_5	0.35	0.43	0.47	0.21	0.47	0.21	0.55	0.38	0.72	0.50	0.47	0.21
	A_1	0.36	0.56	0.47	0.21	0.55	0.38	0.55	0.38	0.60	0.18	0.72	0.50
	A_2	0.42	0.30	0.55	0.38	0.55	0.38	0.55	0.38	0.55	0.38	0.55	0.38
E_3	A_3	0.47	0.21	0.55	0.38	0.60	0.18	0.55	0.38	0.60	0.18	0.83	0.42
	A_4	0.72	0.50	0.72	0.50	0.83	0.42	0.83	0.42	0.83	0.42	0.83	0.42
	A_5	0.35	0.43	0.42	0.30	0.42	0.30	0.55	0.38	0.83	0.42	0.42	0.30
	A_1	0.35	0.43	0.42	0.30	0.50	0.62	0.55	0.38	0.60	0.18	0.83	0.42
	A_2	0.42	0.30	0.50	0.62	0.55	0.38	0.55	0.38	0.50	0.62	0.55	0.38
E_4	A_3	0.72	0.50	0.50	0.62	0.50	0.62	0.60	0.18	0.60	0.18	0.72	0.50
	A_4	0.72	0.50	0.72	0.50	0.60	0.18	0.83	0.42	0.72	0.50	0.83	0.42
	A_5	0.36	0.56	0.47	0.21	0.42	0.30	0.55	0.38	0.60	0.18	0.42	0.30
	A_1	0.35	0.43	0.42	0.30	0.50	0.62	0.50	0.62	0.72	0.50	0.72	0.50
	A_2	0.42	0.30	0.50	0.62	0.55	0.38	0.55	0.38	0.72	0.50	0.50	0.62
E_5	A_3	0.60	0.18	0.50	0.62	0.60	0.18	0.60	0.18	0.60	0.18	0.72	0.50
	A_4	0.72	0.50	0.72	0.50	0.83	0.42	0.83	0.42	0.72	0.50	0.83	0.42
	A_5	0.35	0.43	0.42	0.30	0.42	0.30	0.55	0.38	0.60	0.18	0.42	0.30
	A_1	0.42	0.30	0.55	0.38	0.55	0.38	0.55	0.38	0.72	0.50	0.60	0.18
	A_2	0.47	0.21	0.50	0.62	0.55	0.38	0.55	0.38	0.72	0.50	0.50	0.62
E_6	A_3	0.47	0.21	0.50	0.62	0.50	0.62	0.60	0.18	0.55	0.38	0.72	0.50
	A_4	0.72	0.50	0.72	0.50	0.83	0.42	0.83	0.42	0.72	0.50	0.83	0.42
	A_5	0.35	0.43	0.50	0.62	0.47	0.21	0.60	0.18	0.60	0.18	0.42	0.30
	A_1	0.35	0.43	0.42	0.30	0.50	0.62	0.55	0.38	0.72	0.50	0.60	0.18
	A_2	0.42	0.30	0.60	0.18	0.60	0.18	0.55	0.38	0.83	0.42	0.55	0.38
E_7	A_3	0.60	0.18	0.55	0.38	0.60	0.18	0.55	0.38	0.60	0.18	0.83	0.42
	A_4	0.72	0.50	0.72	0.50	0.83	0.42	0.83	0.42	0.83	0.42	0.83	0.42
	A_5	0.35	0.43	0.42	0.30	0.42	0.30	0.55	0.38	0.83	0.42	0.42	0.30
	A_1	0.36	0.56	0.47	0.21	0.47	0.21	0.55	0.38	0.60	0.18	0.72	0.50
	A_2	0.42	0.30	0.60	0.18	0.60	0.18	0.60	0.18	0.72	0.50	0.55	0.38
E_8	A_3	0.72	0.50	0.55	0.38	0.55	0.38	0.60	0.18	0.55	0.38	0.72	0.50
	A_4	0.72	0.50	0.72	0.50	0.72	0.50	0.83	0.42	0.83	0.42	0.83	0.42
	A_5	0.36	0.56	0.42	0.30	0.47	0.21	0.60	0.18	0.72	0.50	0.42	0.30
	A_1	0.35	0.43	0.42	0.30	0.42	0.30	0.47	0.21	0.50	0.62	0.55	0.38
	A_2	0.47	0.21	0.55	0.38	0.50	0.62	0.60	0.18	0.47	0.21	0.47	0.21
E_9	A_3	0.55	0.38	0.60	0.18	0.60	0.18	0.55	0.38	0.60	0.18	0.83	0.42
	A_4	0.83	0.42	0.83	0.42	0.83	0.42	0.83	0.42	0.83	0.42	0.83	0.42
	A_5	0.35	0.43	0.42	0.30	0.42	0.30	0.55	0.38	0.83	0.42	0.42	0.30
	A_1	0.36	0.56	0.47	0.21	0.50	0.62	0.50	0.62	0.60	0.18	0.47	0.21
	A_2	0.42	0.30	0.42	0.30	0.42	0.30	0.55	0.38	0.50	0.62	0.47	0.21
E_{10}	A_3	0.55	0.38	0.60	0.18	0.55	0.38	0.60	0.18	0.83	0.42	0.72	0.50
	A_4	0.83	0.42	0.72	0.50	0.72	0.50	0.72	0.50	0.83	0.42	0.83	0.42
	A_5	0.40	0.73	0.40	0.73	0.47	0.21	0.55	0.38	0.72	0.50	0.47	0.21

Table 6. The aggregated decision matrix

Alt.	C_1		C_2		C_3		C_4		C_5		C_6	
	$\mu_{\tilde{X}_{id}}(x)$	$\vartheta_{\tilde{X}_{id}}(x)$	$\mu_{\tilde{X}_{id}}(x)$	$\vartheta_{\tilde{X}_{id}}(x)$	$\mu_{\tilde{X}_{id}}(x)$	$\vartheta_{\tilde{X}_{id}}(x)$	$\mu_{\tilde{X}_{id}}(x)$	$\vartheta_{\tilde{X}_{id}}(x)$	$\mu_{\tilde{X}_{id}}(x)$	$\vartheta_{\tilde{X}_{id}}(x)$	$\mu_{\tilde{X}_{id}}(x)$	$\vartheta_{\tilde{X}_{id}}(x)$
A_1	0.3607	0.4687	0.4544	0.2632	0.5060	0.4574	0.5279	0.4324	0.6511	0.3102	0.6959	0.3536
A_2	0.4287	0.2835	0.5447	0.3299	0.5784	0.3088	0.5605	0.3290	0.6975	0.4600	0.5210	0.3983
A_3	0.5921	0.3092	0.5481	0.3791	0.5585	0.3291	0.5817	0.2406	0.6242	0.2509	0.7684	0.4679
A_4	0.7592	0.4743	0.7453	0.4837	0.7960	0.4109	0.8090	0.4374	0.7935	0.4495	0.8300	0.4200
A_5	0.3582	0.4832	0.4356	0.3321	0.4426	0.2579	0.5605	0.3290	0.7451	0.3575	0.4324	0.2765

Table 7. The initial decision matrix for the MEREC method

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.472	0.538	0.517	0.533	0.623	0.646	25	242	3069	5.83
A_2	0.528	0.563	0.582	0.570	0.621	0.539	30	242	3069	5.83
A_3	0.589	0.555	0.569	0.591	0.614	0.676	25	168	3050	5.875
A_4	0.665	0.650	0.717	0.723	0.704	0.749	25	230	3050	5.88
A_5	0.467	0.523	0.535	0.570	0.684	0.530	40	237	4232	8.05

Table 8. The normalized decision matrix

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.989	0.973	1.000	1.000	0.985	0.820	1.000	0.694	0.725	0.724
A_2	0.884	0.929	0.888	0.935	0.988	0.983	0.833	0.694	0.725	0.724
A_3	0.792	0.942	0.908	0.901	1.000	0.784	1.000	1.000	0.721	0.730
A_4	0.701	0.804	0.720	0.737	0.871	0.708	1.000	0.730	0.721	0.730
A_5	1.000	1.000	0.967	0.935	0.897	1.000	0.625	0.709	1.000	1.000

Table 9. The overall performance values of the alternatives

Alternatives	S_i
A_1	0.1189
A_2	0.1487
A_3	0.1291
A_4	0.2347
A_5	0.0975

Table 10. The partial performance values of the alternatives

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.1179	0.1164	0.1189	0.1189	0.1175	0.1011	0.1189	0.0859	0.0899	0.0898
A_2	0.1380	0.1424	0.1384	0.1429	0.1477	0.1472	0.1329	0.1167	0.1206	0.1205
A_3	0.1084	0.1239	0.1206	0.1200	0.1291	0.1075	0.1291	0.1291	0.0999	0.1011
A_4	0.2062	0.2173	0.2084	0.2103	0.2237	0.2069	0.2347	0.2095	0.2084	0.2095
A_5	0.0975	0.0975	0.0944	0.0913	0.0876	0.0975	0.0539	0.0658	0.0975	0.0975

Table 11. The total of absolute deviations and criterion weights

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
T_j	0.0609	0.0315	0.0481	0.0455	0.0232	0.0686	0.0594	0.1218	0.1125	0.1105
$\mathfrak{w}_j$	0.0893	0.0461	0.0706	0.0667	0.0341	0.1006	0.0871	0.1786	0.1649	0.1620
Ranking	5	9	7	8	10	4	6	1	2	3

- **Stage 2:** Ranking of the alternatives based on FF-ARLON method

The initial decision matrix to be used in the ARLON method is shown in Table 12. The first logarithmic normalization matrix is shown in Table 13. and the second logarithmic normalization matrix is shown in Table 14. The normalized decision matrices obtained are aggregated as shown in Table 15. The weighted decision matrix is shown in Table 16. The cost-weighted and benefit-weighted aggregated normalized matrices are shown in Table 17. The final values and the ranking of the alternatives are shown in Table 18.

Table 12. The initial decision matrix for the ARLON method

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	47.20	53.78	51.69	53.31	62.31	64.64	2500.00	24200.00	306900.00	583.00
A_2	52.80	56.28	58.20	57.02	62.10	53.91	3000.00	24200.00	306900.00	583.00
A_3	58.90	55.51	56.93	59.14	61.37	67.57	2500.00	16800.00	305000.00	587.50
A_4	66.54	65.04	71.75	72.29	70.44	74.88	2500.00	23000.00	305000.00	588.00
A_5	46.66	52.30	53.48	57.02	68.40	52.99	4000.00	23700.00	423200.00	805.00

Table 13. The first logarithmic normalization matrix

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.1933	0.1976	0.1943	0.1947	0.1981	0.2018	0.1967	0.2017	0.2002	0.2005
A_2	0.1989	0.1999	0.2002	0.1980	0.1979	0.1930	0.2013	0.2017	0.2002	0.2005
A_3	0.2044	0.1992	0.1991	0.1998	0.1974	0.2040	0.1967	0.1945	0.2003	0.2005
A_4	0.2105	0.2071	0.2105	0.2096	0.2040	0.2090	0.1967	0.2007	0.2003	0.2005
A_5	0.1927	0.1962	0.1960	0.1980	0.2026	0.1922	0.2085	0.2013	0.1990	0.1980

Table 14. The second logarithmic normalization matrix

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.1933	0.1976	0.1943	0.1947	0.1981	0.2018	0.1967	0.2017	0.8010	0.8021
A_2	0.1989	0.1999	0.2002	0.1980	0.1979	0.1930	0.2013	0.2017	0.8010	0.8021
A_3	0.2044	0.1992	0.1991	0.1998	0.1974	0.2040	0.1967	0.1945	0.8011	0.8019
A_4	0.2105	0.2071	0.2105	0.2096	0.2040	0.2090	0.1967	0.2007	0.8011	0.8018
A_5	0.1927	0.1962	0.1960	0.1980	0.2026	0.1922	0.2085	0.2013	0.7959	0.7921

Table 15. The aggregated normalized decision matrix

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.1933	0.1976	0.1943	0.1947	0.1981	0.2018	0.1967	0.2017	0.4505	0.4512
A_2	0.1989	0.1999	0.2002	0.1980	0.1979	0.1930	0.2013	0.2017	0.4505	0.4512
A_3	0.2044	0.1992	0.1991	0.1998	0.1974	0.2040	0.1967	0.1945	0.4506	0.4511
A_4	0.2105	0.2071	0.2105	0.2096	0.2040	0.2090	0.1967	0.2007	0.4506	0.4510
A_5	0.1927	0.1962	0.1960	0.1980	0.2026	0.1922	0.2085	0.2013	0.4477	0.4455

Table 16. The weighted aggregated normalization matrix

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	0.0173	0.0091	0.0137	0.0130	0.0067	0.0203	0.0171	0.0360	0.0743	0.0731
A_2	0.0178	0.0092	0.0141	0.0132	0.0067	0.0194	0.0175	0.0360	0.0743	0.0731
A_3	0.0183	0.0092	0.0140	0.0133	0.0067	0.0205	0.0171	0.0347	0.0743	0.0731
A_4	0.0188	0.0096	0.0149	0.0140	0.0069	0.0210	0.0171	0.0358	0.0743	0.0731
A_5	0.0172	0.0091	0.0138	0.0132	0.0069	0.0193	0.0182	0.0359	0.0738	0.0722

Table 17. The cost-weighted and benefit-weighted aggregated normalized matrix

Alternatives	A_1	A_2	A_3	A_4	A_5
$\mathcal{C}_i^-$	0.1474	0.1474	0.1474	0.1474	0.1460
$\mathcal{B}_i^+$	0.1333	0.1340	0.1339	0.1381	0.1337

Table 18. The final values and the ranking

Alternatives	A_1	A_2	A_3	A_4	A_5
G_i	0.88133	0.88223	0.88207	0.88709	0.88048
$\mathbb{R}_i$	0.1290	0.2642	0.2406	1.0000	0.0000
Ranking	4	2	3	1	5

4.2 Sensitivity and Comparative Analysis

4.2.1 Sensitivity analysis

Two different sensitivity analysis scenarios were applied to test the robustness of the study. In the first scenario, the steps were repeated by changing the tradeoff ratio value in the ARLON method. The results obtained are shown in Figure 1. In the second scenario, each criterion was removed from the problem one by one, and the steps were repeated. The results obtained are shown in Figure 2. In both scenarios, the best alternative has been determined to be the fourth alternative.

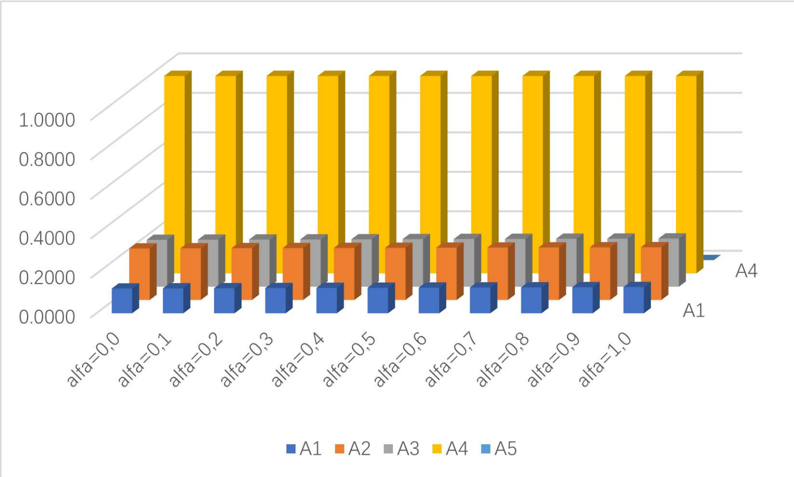

Figure 1. Sensitivity analysis scenario-1

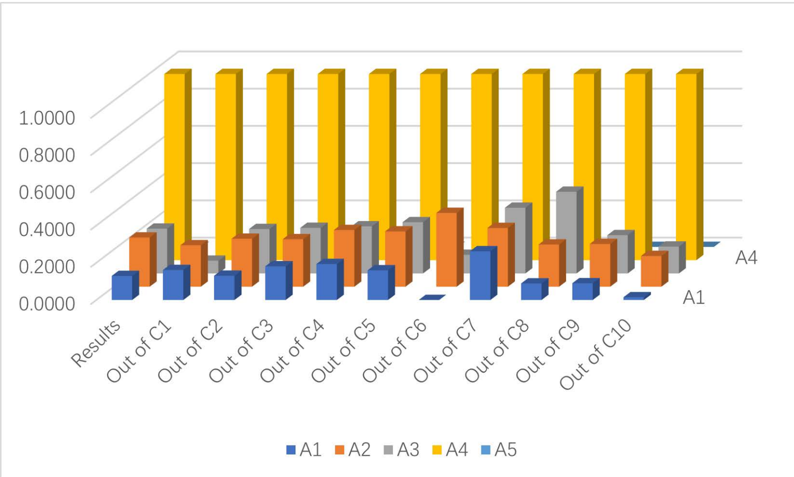

Figure 2. Sensitivity analysis scenario-2

4.2.2 Comparative analysis

The study was compared with 8 different MCDM methods. The methods used in the comparative analysis are: ALWAS [31], AROMAN [32], ARTASI [33], MABAC [34], MARCOS [35], RAM [36], SAW [37], and WASPAS [38]. The results obtained from the comparative analysis are shown in Figure 3. According to the results obtained, the best alternative in all methods is the same as the ARLON method used in the study and has been determined as the 4th alternative.

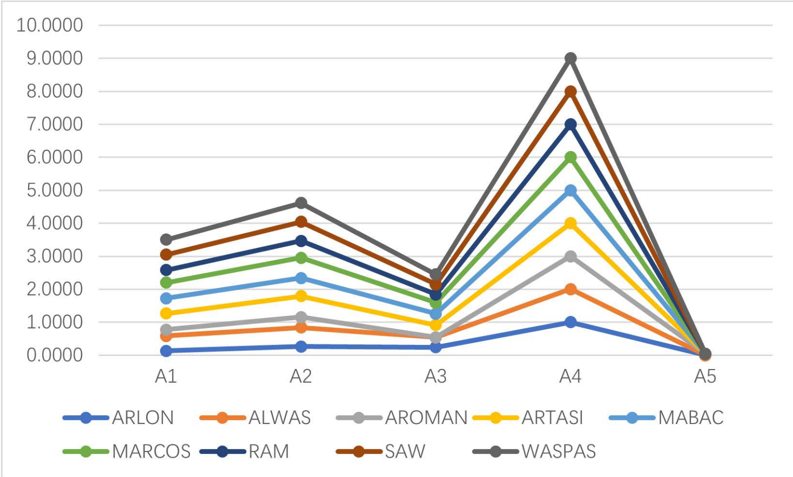

Figure 3. Comparative analysis

5 Results

The proposed FF-Hamacher-MEREC-ARLON framework was applied to evaluate five forklift alternatives used in CFS operations. The MEREC results indicate that technical performance criteria, particularly motor power, overall width, and turning radius, have the highest importance weights, while ESG indicators show moderate but meaningful influence. Based on these weights, the ARLON ranking method identified Alternative 4 as the best-performing option.

To assess the robustness of the findings, two sensitivity analyses were conducted. In the first scenario, changing the tradeoff ratio within the ARLON method did not alter the ranking results. In the second scenario, each criterion was removed sequentially and the entire process recalculated; Alternative 4 again remained the top-ranked choice. Additionally, comparative analyses with eight established MCDM methods (ALWAS, AROMAN, ARTASI, MABAC, MARCOS, RAM, SAW, and WASPAS) produced identical rankings, further validating the consistency and reliability of the proposed model. Overall, the results demonstrate that the hybrid framework provides stable, reproducible, and sustainability-aligned outcomes for heavy-duty forklift selection.

6 Conclusions

This study proposes a comprehensive hybrid decision-making framework integrating FF-Hamacher aggregation, the MEREC weighting technique, and the ARLON ranking method to support the sustainable and high-performance selection of heavy-duty forklifts used in Container Freight Station (CFS) operations. The increasing emphasis on environmentally responsible port management, combined with the operational challenges of handling cargo exceeding 25 tons, necessitates a multidimensional evaluation structure that simultaneously addresses technical, environmental, social, and governance-related criteria. The developed model effectively captures expert uncertainty through FF sets, ensures objective determination of criterion weights using the MEREC approach, and provides a robust prioritization of alternatives through the ARLON method.

The empirical results demonstrate that technical performance indicators, particularly lifting capacity, motor power, overall width, and turning radius, constitute the most influential criteria in forklift selection, while sustainability-driven factors such as emission and fuel consumption also play a significant role. Among the evaluated alternatives, Alternative 4 consistently achieved the highest performance score across the primary analysis, sensitivity tests, and comparative assessments. Two extensive sensitivity analyses confirmed that the final ranking remained unchanged under variations in the ARLON tradeoff ratio and the exclusion of individual criteria, reinforcing the stability of the model. Furthermore, comparative analysis with eight established MCDM methods (ALWAS, AROMAN, ARTASI, MABAC, MARCOS, RAM, SAW, and WASPAS) yielded identical results, validating the reliability and methodological soundness of the proposed hybrid approach.

Overall, the findings highlight the strategic importance of incorporating ESG-based indicators into equipment selection processes in modern port operations. The proposed framework not only enhances decision accuracy but also aligns equipment procurement decisions with green port transformation policies. Future research may extend this approach to other types of port equipment, explore dynamic or real-time expert evaluation mechanisms, or integrate life-cycle assessment metrics to further strengthen sustainability-oriented decision-making in maritime logistics.

Author Contributions

Conceptualization, G.C.Y., K.K., and P.G.; methodology, G.C.Y., K.K., and P.G.; validation, G.C.Y., K.K., P.G., and M.B.; formal analysis, G.C.Y., K.K., P.G., and M.B.; resources, G.C.Y., K.K., P.G., and M.B.; data curation, G.C.Y., K.K., and P.G.; writing—original draft preparation, G.C.Y., K.K., P.G., and M.B.; writing—review and editing, G.C.Y., K.K., P.G., and M.B.; visualization, G.C.Y., K.K., P.G., and M.B.; project administration, G.C.Y. and P.G.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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