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Research Article

Sustainability Analysis of Dispatcher Flight Routing Using Hybrid Fuzzy Method

Ümit Kanmaz *

Istanbul Ticaret University, Department of Aviation Management, Istanbul, Turkiye
ukanmaz@ticaret.edu.tr- *0000-0003-2186-2737*

Abstract

This study proposes a hybrid fuzzy multi-criteria decision-making (MCDM) approach to evaluate the sustainability impacts of dispatcher-optimized flight routing in aviation. The model integrates the Fuzzy Best-Worst Method (FBWM) for determining the relative importance of sustainability criteria and the Fuzzy MARCOS method for ranking routing alternatives. Data were collected from 11 aviation experts in Türkiye, including dispatchers, pilots, and fuel managers, ensuring a practical and multi-perspective evaluation. Seven criteria were considered: fuel consumption, CO_2 emissions, safety, cost efficiency, flight time, air traffic management (ATM) compatibility, and passenger comfort. The results demonstrate that Collaborative ATM-Integrated Routing is the most sustainable option, followed by Dynamic Weather-Adaptive Routing, while Standard Pre-Filed Routing ranked lowest. Sensitivity analysis confirmed the robustness of the rankings across different weighting scenarios. These findings emphasize the critical role of dispatchers in shaping aviation sustainability outcomes and provide actionable insights for airlines, regulators, and policymakers in aligning operational practices with long-term net-zero and environmental goals. The study contributes to the literature by integrating operational decision-making into sustainability evaluations and offering a replicable methodological framework for future aviation studies.

Keywords

Dispatcher Routing
Aviation Sustainability
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1. Introduction

Aviation contributes about 2–3% of global CO_2 emissions, with projections indicating further growth without targeted interventions (McKinsey, 2023; EESI, 2025; FAA, 2021). While long-term solutions such as sustainable aviation fuels (SAFs), electric propulsion, and advanced aircraft designs are under development (Qasem et al., 2024; Song et al., 2024; Khalifa et al., 2024; Valdés & Comendador, 2025), operational measures provide immediate, cost-effective opportunities to curb emissions, particularly through enhanced flight planning and dispatch (Calvet, 2024; SESAR Joint Undertaking, 2024).

Despite their central role in balancing fuel efficiency, safety, weather, and airspace constraints, dispatchers remain underrepresented in sustainability research (Bertelli Fogaça et al., 2022; Nechesa, 2023). Most prior studies emphasize pilots, air traffic control, or isolated optimization aspects such as trajectory management, disruption recovery, or alternative fuels (Rosenow et al., 2021), but few holistically assess dispatcher-led routing across environmental, operational, and passenger-related dimensions.

This study addresses that gap with two objectives: (1) to evaluate the multi-dimensional sustainability impacts of dispatcher-based routing decisions, and (2) to apply a hybrid fuzzy multi-criteria decision-making (MCDM) framework—combining Fuzzy Best-Worst Method (FBWM) and Fuzzy MARCOS—to prioritize routing alternatives based on expert judgments from practitioners in Türkiye. The hybrid approach accommodates uncertainty in expert evaluations while ensuring systematic prioritization of competing criteria.

The study contributes by: (i) extending fuzzy MCDM methods to dispatcher routing optimization, building on prior applications in technology evaluation, disruption management, and infrastructure planning (Markatos et al., 2023; Alharasees & Kale, 2024; Montlaur et al., 2023; Seker, 2025); (ii) providing a holistic assessment that integrates environmental, economic, safety, operational, and passenger criteria; and (iii) offering managerial and policy insights that highlight the near-term value

*: Corresponding Author Umit Kanmaz, ukanmaz@ticaret.edu.tr
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of advanced routing while aligning with longer-term decarbonization agendas (IATA, 2025).

By bridging theoretical advances in fuzzy MCDM with the operational realities of airline dispatch, this research delivers both academic and practical value, supporting more sustainable and efficient flight planning in the transition toward net-zero aviation.

2. Literature Review

2.1. Dispatcher Routing in Aviation Operations

In modern aviation, dispatchers have evolved into central decision-makers responsible for real-time operational optimization that integrates fuel efficiency, safety, air traffic management, and environmental sustainability. According to Calvet (2024), dispatchers no longer perform static pre-flight planning but continuously monitor and adjust flight paths during all phases of flight, balancing economic and ecological objectives while maintaining safety margins. The complexity of this role has grown as global air traffic volumes increase, making operational inefficiencies highly consequential (Calvet, 2024). One of the most impactful advances in dispatcher operations is in-flight trajectory optimization, allowing dispatchers to collaborate with pilots and air traffic control to reroute aircraft dynamically in response to changing meteorological and airspace conditions (Rosenow et al., 2021). This dynamic coordination leads to significant fuel savings and emission reductions, with Rosenow et al. (2021) estimating that optimized trajectories can reduce fuel burn by up to 5% on certain long-haul routes. Furthermore, dispatcher roles extend to managing disruptions caused by weather, technical malfunctions, or congestion. As Bertelli Fogaça et al. (2022) illustrate, dispatchers in operational control centers make rapid, high-stakes decisions under complex and uncertain conditions, balancing flight punctuality, safety, passenger connections, and fuel efficiency. Their cognitive skills, experience, and situational awareness remain indispensable, even as advanced decision-support systems aid scenario modeling and forecasting (Bertelli Fogaça et al., 2022).

The complexity of dispatcher routing intensifies when aircraft require mid-flight rerouting due to unforeseen events like adverse weather or temporary airspace restrictions. Goncharenko et al. (2021) emphasize that these real-time deviations demand rapid evaluation of fuel burn projections, arrival adjustments, and separation requirements, often necessitating probabilistic models to handle random event streams while ensuring safety. Concurrently, trajectory-based operations (TBO) have introduced performance-optimized, four-dimensional trajectories that integrate spatial, temporal, and environmental factors into continuous flight management. Álvarez and De Oliveira (2025) note that successful TBO deployment depends heavily on dispatcher collaboration with pilots and air traffic controllers to adjust flight paths dynamically, leading to improved predictability, smoother traffic flows, and lower fuel consumption. This strategic role places dispatchers at the forefront of aviation sustainability efforts, directly supporting global decarbonization goals. Moreover, dispatchers are now addressing non-CO_2 climate effects, such as contrail formation. Frias et al. (2024) demonstrate that integrating contrail avoidance algorithms into dispatcher planning allows flights to avoid atmospheric conditions prone to contrail generation, reducing short-term radiative forcing impacts while still preserving fuel efficiency and operational safety.

At the regulatory and airspace management level, dispatcher responsibilities have also expanded due to the implementation of Free Route Airspace (FRA) in regions like Europe. FRA allows aircraft to bypass fixed airways and select optimal routing between entry and exit points, offering substantial fuel and emissions savings. However, as Nechesa (2023) explains, this flexibility significantly increases conflict detection complexity during flight planning, requiring dispatchers to collaborate closely with air navigation service providers to resolve potential conflicts while maximizing operational efficiency. The adoption of FRA thus enhances routing efficiency but elevates dispatcher workload and decision-making complexity. Collectively, these developments position dispatchers as critical agents driving both operational resilience and sustainability improvements in aviation, balancing multiple performance objectives under increasingly sophisticated airspace and environmental frameworks (Nechesa, 2023).

2.2. Fuel Efficiency, Emissions, and Aviation Sustainability

Aviation sustainability has become a major global challenge, with the sector contributing approximately 2.5% of global CO_2 emissions and facing mounting regulatory and societal pressure to decarbonize (Jiang et al., 2024). Improving fuel efficiency remains one of the most critical pillars in reducing aviation's environmental impact, as fuel combustion directly correlates with emissions. While historic advances in aircraft design, engine technologies, and operational optimization have delivered substantial efficiency gains, these have not fully offset growing passenger and cargo demand (Valdés and Comendador, 2025). Dispatchers play an important role in fuel efficiency by optimizing payload, fuel uplift, and aircraft weight, since small variations in takeoff mass significantly affect fuel burn across the entire flight profile (Zou et al., 2025). Complementing dispatcher interventions, multiple air traffic management (ATM) programs such as Europe's SESAR and the U.S. NextGen have deployed direct routing, continuous climb and descent operations, and performance-based navigation systems that together achieve up to 10% global fuel savings when fully realized (SESAR Joint Undertaking, 2024; FAA, 2021; EESI, 2025; McKinsey, 2023). Continuous descent operations at major airports have already saved millions of gallons of fuel (FAA, 2022), while cruise altitude optimization further enhances fuel efficiency on long-haul routes (Ekici et al., 2024). These operational improvements offer immediate and cost-effective emissions reductions while technological solutions continue to mature.

Despite these important operational gains, full decarbonization requires more transformative technological advances. Sustainable Aviation Fuels (SAF), which can reduce lifecycle emissions by 70–100% compared to fossil-based Jet-A depending on production pathway, represent the most viable mid-term solution (Song et al., 2024; Qasem et al., 2024). Global policy frameworks reflect SAF's importance: the U.S. Aviation Climate Action Plan targets 3 billion gallons of SAF production by 2030 and full replacement by 2050 (FAA, 2021), while the EU's ReFuelEU Aviation Initiative mandates a 70% SAF blend by 2050 (European Commission, 2024). Nevertheless, SAF faces cost and scale-up challenges, being 3–5 times more expensive than conventional jet fuel due to limited feedstocks, immature supply chains, and capital-intensive production (IATA, 2025). Airlines have responded with long-term procurement commitments, underscoring SAF's critical role in decarbonization pathways. Meanwhile, aircraft manufacturers and agencies like NASA are developing new airframe designs such as transonic truss-braced wings and open-rotor engines capable of delivering 20–30% additional fuel savings beyond current models (NASA, 2024; Alharasees and Kale, 2024). Fleet renewal through adoption of A320neo and 737 MAX aircraft has already delivered 15–20% per-seat fuel savings (McKinsey, 2023; FAA, 2021), providing near-term operational benefits while more advanced designs mature for commercial deployment in the 2030s.

Longer-term zero-emission technologies, such as hydrogen propulsion and battery-electric aircraft, remain in earlier stages of development. Hydrogen-powered aircraft, as exemplified by Airbus's delayed ZEROe program, may not enter commercial service before 2040 (GreenAir News, 2024), while battery-electric aircraft remain restricted to short-range, low-capacity markets due to current energy density limitations (FAA, 2021; Avogadro and Redondi, 2024). Circular economy approaches, including closed-loop recycling, sustainable materials, and efficient maintenance processes, also contribute to lifecycle emissions reductions (Khalifa et al., 2024). To manage residual emissions that remain difficult to eliminate technologically, ICAO's CORSIA program and emerging carbon removal technologies such as direct air capture are increasingly important (Jiang et al., 2024; IATA, 2025). As EESI (2025), McKinsey (2023) emphasize, achieving aviation sustainability will require synchronized deployment of operational improvements, SAF scaling, next-generation aircraft, and advanced carbon removal solutions between 2030 and 2050, supported by coordinated global policies, industry investment, and regulatory frameworks.

2.3. MCDM Applications in Aviation

The growing complexity of aviation operations and sustainability challenges has made Multi-Criteria Decision-Making (MCDM) methods increasingly essential for managing the sector's multi-dimensional decision processes (Markatos et al., 2023). Aviation stakeholders face trade-offs involving safety, cost, environmental impact, efficiency, and technological readiness, which MCDM models systematically evaluate by integrating both quantitative and qualitative criteria. Hybrid MCDM approaches, combining techniques like fuzzy AHP, TOPSIS, and SWARA, have been successfully applied across domains such as sustainable aviation fuel (SAF) selection, airline operations, and fleet management (Chai and Zhou, 2022; Seker, 2025). For example, Chai and Zhou (2022) used a hybrid fuzzy AHP-TOPSIS framework to evaluate SAF alternatives based on feedstock availability, lifecycle emissions, production cost, and policy readiness, while Seker (2025) applied an MCDM model to assess the agile attributes of low-cost carriers, emphasizing digitalization, environmental responsiveness, and operational flexibility as drivers of sustainable competitiveness.

Beyond fuel and business model evaluation, MCDM frameworks have expanded into maintenance, disruption management, flight crew decision-support, and load optimization. Aslan and Tolga (2022) applied MCDM to assess AI applications in Maintenance, Repair, and Overhaul (MRO) operations, balancing predictive maintenance efficiency, cost, and human integration. Uzgör et al. (2024) used R-SWARA to prioritize decision factors in disruption management, helping airlines handle delays and irregular operations while maintaining customer satisfaction. Similarly, Montlaur et al. (2023) developed a domain-driven MCDM model for flight crews, integrating real-time safety, workload, and operational constraints to support cockpit decision-making under uncertainty. Alharasees and Kale (2024) addressed aviation operators' total load analysis, where MCDM tools balanced payload maximization, fuel burn, route design, and regulatory compliance to achieve fuel-efficient, environmentally aligned operational outcomes.

MCDM applications also inform strategic-level decisions in aviation infrastructure, fleet planning, and supply chain management. Lee et al. (2018) proposed an MCDM framework for selecting green fleet programs, integrating acquisition cost, environmental impact, and operational feasibility, while Zhang et al. (2020) applied hybrid heuristics with particle swarm optimization to location-routing problems under fuzzy demand in aviation logistics. Collectively, these studies illustrate that MCDM methodologies provide robust frameworks for navigating the complex, multi-layered trade-offs inherent in sustainable aviation transformation. As aviation confronts growing decarbonization pressures, MCDM continues to offer essential tools for balancing operational resilience, digital transformation, technological innovation, and environmental performance across the aviation ecosystem.

3. Methodology

3.1. Research Design

This study adopts a mixed-method approach that combines expert judgment with operational data to evaluate the sustainability impacts of dispatcher-determined flight routing in aviation operations. The mixed-method design is particularly appropriate for addressing complex aviation sustainability problems that involve both quantitative (e.g., fuel consumption, emissions data) and qualitative (e.g., expert assessments, subjective trade-offs) components (Plano Clark, 2017). By integrating multiple data sources, the study ensures comprehensive analysis while maintaining methodological rigor. Multi-Criteria Decision-Making (MCDM) serves as the central analytical framework to structure the evaluation, allowing the synthesis of operational, economic, safety, and environmental factors into a unified assessment model (Markatos et al., 2023; Chai and Zhou, 2022). The research process consists of four key stages: (i) identification and validation of evaluation criteria; (ii) expert data collection via structured Delphi rounds and weighting assignments; (iii) collection of real-world and simulated flight operational data (including fuel consumption, routing efficiency, and emissions); and (iv) application of a hybrid MCDM model to derive prioritization and trade-off results. The combination of expert elicitation and operational data ensures that both strategic-level and practical operational factors are adequately captured in the analysis.

3.2. Criteria Identification

The identification of evaluation criteria is grounded in an extensive review of the literature on aviation sustainability, dispatcher operations, and flight optimization. Based on prior studies (Zou et al., 2025; Valdés and Comendador, 2025; Ekici et al., 2024; Markatos et al., 2023; Chai and Zhou, 2022; Seker, 2025), four main dimensions were established: environmental, operational, economic, and safety-related criteria. Table 1 summarizes the identified criteria and their supporting literature.

To validate and finalize the criteria, the Delphi technique was employed with participation from the expert panel. The Delphi method is particularly suitable for deriving consensus on complex, multi-dimensional issues where empirical data alone may not fully capture the decision landscape (Hsu and Sandford, 2007). Two iterative rounds of feedback were conducted to refine, adjust, and confirm the relevance and comprehensiveness of the selected criteria before moving into the MCDM modeling stage.

3.3. Data Collection

The expert panel consists of 11 professionals from Türkiye, selected for their expertise and operational roles related to flight dispatch, fuel planning, flight operations, and flight crew management. The panel includes dispatchers, pilots, fuel planning managers, and operations officers, ensuring comprehensive perspectives from both planning and execution domains. Table 2 included information about experts participated in the panel. In determining the sufficient number of experts, this study adopted a balance between methodological rigor and practical feasibility. The selection of eleven experts was guided by established practices in multi-criteria decision-making (MCDM) and fuzzy decision-making applications, where panels typically range from 8 to 15 experts to ensure both diversity of opinion and analytical manageability (Ishizaka & Nemery, 2013; Büyüközkan & Göçer, 2018). This range is frequently cited in the literature as sufficient to capture heterogeneous perspectives without leading to excessive inconsistency in pairwise comparisons or weighting procedures.

The choice of this number also aligns with the study's criteria set. While the number of experts was not directly determined by the number of criteria, the decision considered the need for balanced representation across operational domains such as dispatch, piloting, and fuel planning. Furthermore, limiting the panel to eleven experts provided a manageable size for consensus-building and consistency checks, both of which are crucial in fuzzy MCDM approaches. A smaller panel may have risked insufficient diversity, while a larger panel could have introduced challenges in harmonizing evaluations and increased the risk of data noise. Thus, the chosen number represents an optimal balance, supporting both the methodological integrity of the analysis and the practical engagement of the experts involved.

Table 1. Evaluation Criteria and References

Dimension	Criterion	Supporting Literature
Environmental	CO_2 Emissions Reduction	Zou et al. (2025); Qasem et al. (2024); Song et al. (2024)
Environmental	Contrail Avoidance Potential	Frias et al. (2024); Ekici et al. (2024)
Operational	Fuel Consumption Efficiency	Ekici et al. (2024); Rosenow et al. (2021)
Operational	Flight Time Reduction	Álvarez and De Oliveira (2025); Montlaur et al. (2023)
Economic	Direct Operational Cost (DOC)	Markatos et al. (2023); Valdés and Comendador (2025)
Economic	Dispatch Flexibility/Adaptability	Bertelli Fogaça et al. (2022); Goncharenko et al. (2021)
Safety	Conflict Avoidance Capability	Nechesa (2023); Montlaur et al. (2023)
Safety	ATC Compliance and Airspace Safety	Markatos et al. (2023); Uzgör et al. (2024)

Table 2. Expert Panel Profile

Expert Code	Position Title	Role	Years of Experience	Organization Type
E1	Senior Dispatcher	Route Planning & Fuel Ops	18	Airline
E2	Flight Operations Manager	Dispatch Oversight & Strategic Ops	20	Airline
E3	Captain Pilot (A330)	Flight Execution & Route Feedback	22	Airline
E4	Fuel Planning Manager	Fuel Calculation & Load Planning	15	Ground Handling
E5	Dispatcher Supervisor	Flight Planning Oversight	19	Airline
E6	Captain Pilot (B777)	Real-Time Operational Adjustments	24	Airline
E7	Operations Control Officer	Disruption Management	17	Airline
E8	Safety & Risk Analyst	Operational Risk Analysis	14	Civil Aviation Authority
E9	Senior ATC Controller	Airspace Flow Optimization	21	ANSP (Türkiye)
E10	Flight Data Analyst	Operational Performance Analysis	12	Airport Authority
E11	Regulatory Expert	Compliance & Policy	16	Civil Aviation Authority

3.4. Analytical Framework Overview

This study employs a hybrid Fuzzy Multi-Criteria Decision-Making (MCDM) framework to systematically evaluate dispatcher-based routing alternatives in aviation operations from a sustainability perspective. The analytical framework integrates expert-based subjective evaluations and operational performance data, enabling a comprehensive assessment under uncertainty and vagueness inherent in real-world aviation operations. The hybrid framework consists of three major stages: (i) fuzzy criteria weighting using the Fuzzy Best-Worst Method (FBWM), (ii) evaluation and ranking of alternatives using the Fuzzy MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) approach, and (iii) sensitivity analysis to assess the robustness of the model against changes in input weight parameters. The full mathematical structure and formulations are presented systematically in Appendices A, B, and C, with notations detailed in Table D1 and linguistic scales in Appendix D.

3.4.1 Stage 1: Criteria Weighting Using Fuzzy Best-Worst Method (FBWM)

The weighting of the identified evaluation criteria was conducted through the Fuzzy Best-Worst Method (FBWM), which offers a more consistent and cognitively efficient approach compared to full pairwise comparison methods. Initially, expert participants selected the most important (best) and least important (worst) criteria from the established list (see Table in Section 3.2), which includes environmental, operational, economic, and safety dimensions critical for dispatcher routing optimization. This step does not imply that a single criterion is universally optimal or negligible; rather, it reflects each expert's subjective judgment in defining the boundaries for the pairwise comparison process. The "best" criterion anchors the evaluation as the most influential factor for sustainability in dispatcher-optimized flight routing, while the "worst" criterion anchors the opposite end of the spectrum. These selections then served as reference points in constructing the comparison vectors that determine the relative weights of all criteria in a consistent manner (Rezaei, 2015).Subsequently, two sets of pairwise comparisons were collected. The best-to-others comparisons are expressed as:

$$\tilde{a}_{Bj},\ j = 1,2,\ldots,m \tag{A1}$$

where $\tilde{a}_{Bj}$ denotes the fuzzy preference of the best criterion B over criterion j. Similarly, others-to-worst comparisons were defined (see Equation A. 2 in Appendix A).

These fuzzy judgments served as input for solving the FBWM optimization model, where the objective is to minimize inconsistencies in expert evaluations:

$$\min \max_j \left| \frac{w_B}{w_j} - \tilde{a}_{Bj} \right| \tag{A3}$$

subject to the normalization and non-negativity conditions described in Equation A. 4 (Appendix A). Once the optimal fuzzy weights $\tilde{w}_j$ were obtained, they were defuzzified into crisp values using the Center of Gravity (COG) method:

$$w_j = \frac{l_j + m_j + u_j}{3} \tag{A5}$$

where l_j, m_j, u_j are the lower, middle, and upper values of the triangular fuzzy weight. Finally, the reliability of the results was assessed by calculating the Fuzzy Consistency Ratio (FCR) (see Equation A. 6 in Appendix A), ensuring that expert judgments were both consistent and robust.

3.4.2 Stage 2: Alternative Evaluation and Ranking Using Fuzzy MARCOS

Following the determination of fuzzy weights, dispatcher routing alternatives were evaluated through the Fuzzy MARCOS method. This method incorporates the compromise ratio principle by considering both ideal and anti-ideal solutions to improve the robustness and precision of ranking.

The process begins with the construction of a fuzzy decision matrix:

$$\tilde{X} = \left[\tilde{x}_{ij}\right]_{m\times n} \tag{B1}$$

where each element $\tilde{x}_{ij}$ represents the fuzzy performance rating of alternative A_i with respect to criterion C_j. These ratings were derived from expert judgments using predefined linguistic terms converted into triangular fuzzy numbers (TFNs), as shown in Appendix D.

The ideal and anti-ideal solutions were then determined according to Equations (B2) and (B3) in Appendix B, which identify the best and worst reference values across criteria.

To enable comparison, the decision matrix was normalized. For benefit criteria, normalization was conducted as:

$$\tilde{x}_{ij}^{n} = \frac{\tilde{x}_{ij}}{\max \tilde{x}_{ij}} \tag{B4}$$

while cost criteria followed the adjustment in Equation (B5, Appendix B). These steps transform the evaluations into a dimensionless scale suitable for aggregation.

The resulting normalized fuzzy matrix was then multiplied by the corresponding weights obtained from FBWM, producing the weighted normalized decision matrix (Equation B6). Overall performance scores were derived using Equation B7, with utility degrees relative to the ideal and anti-ideal solutions calculated via Equations B8-B9.

Finally, the fuzzy utility values were defuzzified using the Center of Gravity (COG) method:

$$U_i = \frac{l_i + m_i + u_i}{3} \tag{B10}$$

Where l_i, m_i, u_i denote the lower, middle, and upper bounds of the fuzzy number for alternative i. The resulting crisp scores enabled the final ranking of dispatcher routing strategies.

3.4.3 Stage 3: Robustness Testing via Sensitivity Analysis

Recognizing the influence of expert judgments and subjective uncertainties, sensitivity analysis was incorporated as a robustness-checking mechanism for the hybrid model. Specifically, the sensitivity procedure tested how perturbations in individual criterion weights affected the final rankings of dispatcher routing alternatives.

The analysis followed a controlled scenario-based approach, where the weight of each criterion was systematically varied by $\pm 5\%, \pm 10\%$, and $\pm 20\%$. The perturbed weight of a given criterion j is expressed as:

$$w_j^{*} = w_j + \Delta \tag{C1}$$

The remaining criteria were proportionally adjusted using the formulation in Equation C. 2 (Appendix C) to maintain weight balance. Importantly, the total weights always satisfied the consistency condition:

$$\sum_{j=1}^{m} w_j' = 1 \qquad \text{(C3)}$$

The range of variation was bounded within practical expert judgment limits (see Equation C. 4 in Appendix C), ensuring that stress testing remained both meaningful and realistic.

In each scenario, the MARCOS procedure was re-run to track ranking stability. To quantify the impact of each criterion, a sensitivity index was also computed:

$$S_j = \frac{\Delta R}{\Delta w_j} \qquad \text{(C5)}$$

This procedure not only confirmed the robustness of the results but also highlighted the most influential criteria, providing practical insights into which sustainability dimensions are most sensitive to expert perception.

4. Results

4.1 FBWM Weighting Results

This research applies the Fuzzy Best-Worst Method (FBWM) to quantify the importance of seven evaluation criteria used in ranking dispatcher routing alternatives for sustainable aviation. The weighting process was conducted by synthesizing the judgments of 11 aviation experts (dispatchers, pilots, fuel managers, and operational officers), who provided paired comparisons based on their professional experience and operational expertise. The FBWM model follows the formulation described in Appendix A (Equations A.1–A.6), transforming expert linguistic judgments into triangular fuzzy numbers, aggregating them using the fuzzy geometric mean, and finally deriving the crisp optimal weights via defuzzification. The resulting weights for each criterion are presented in Table 3. The analysis demonstrates that Fuel Consumption Reduction (C1) received the highest importance weight (22.6%), reflecting the strong emphasis placed on minimizing fuel burn, which directly correlates with both environmental and economic benefits.

Table 3. FBWM-Derived Criteria Weights

Code	Criteria	Final Weight (Wi)
C1	Fuel Consumption Reduction	0.226
C2	CO_2 Emissions Reduction	0.203
C3	Flight Safety and Risk Mitigation	0.176
C4	Operational Cost Efficiency	0.136
C5	Flight Time Optimization	0.110
C6	ATM Compatibility	0.088
C7	Passenger Comfort & Scheduling Reliability	0.061

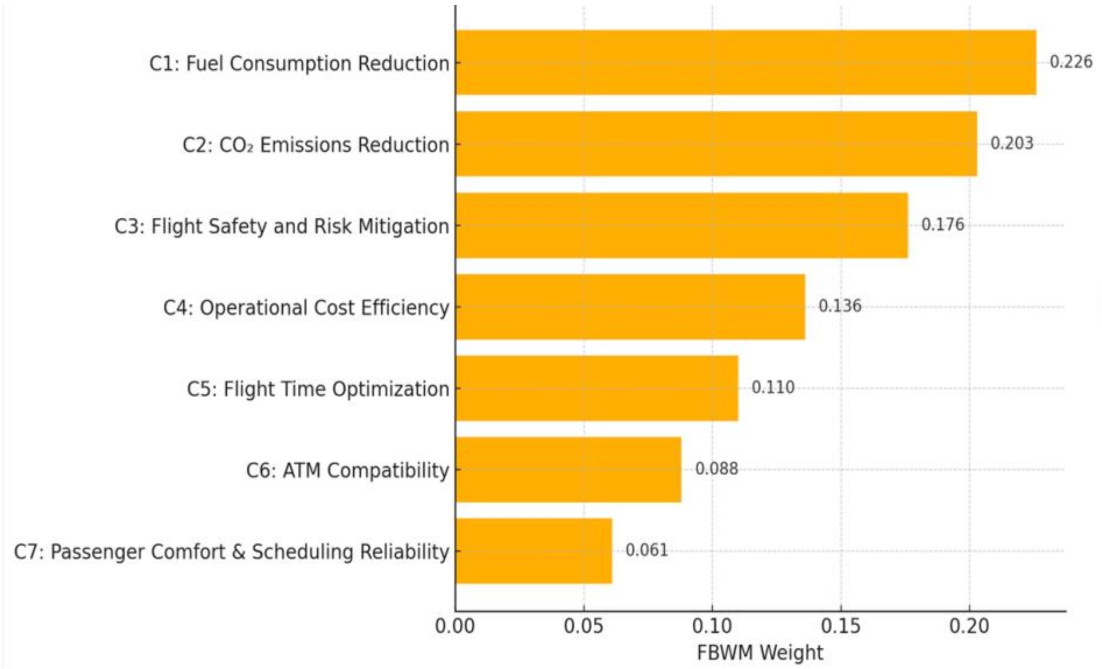

Fig 1 . Distribution of FBWM Criteria Weights

Closely following is CO_2 Emissions Reduction (C2) at 20.3%, highlighting the strategic priority of global aviation decarbonization objectives, in alignment with ICAO and IATA net-zero targets (IATA, 2021; ICAO, 2022). Flight Safety and Risk Mitigation (C3) was ranked third (17.6%), confirming that while sustainability is critical, operational safety remains a non-negotiable foundation in dispatcher route planning decisions. Operational Cost Efficiency (C4) and Flight Time Optimization (C5) hold moderate weights (13.6% and 11.0%, respectively), capturing the balance that dispatchers must maintain between profitability and schedule adherence The relatively lower weights assigned to ATM Compatibility (C6) and Passenger Comfort & Scheduling Reliability (C7) (8.8% and 6.1%) suggest that, while important, these factors are perceived as less critical than fuel, emissions, and safety considerations when optimizing dispatcher routing from a sustainability perspective. The overall consistency index derived during FBWM optimization was below the acceptable threshold (Consistency Index $\leq$ 0.05), indicating high internal consistency across expert judgments. Additionally, variance analysis across experts showed that the relative ranking of criteria was broadly shared among dispatchers and operational experts, confirming a strong professional consensus regarding the multi-dimensional trade-offs involved in sustainable dispatcher routing. For better clarity, the final weight distribution is illustrated in Figure 1.

The results presented in Table 3 and Figure 1 reveal the relative weight distribution of the evaluation criteria. As expected, operational efficiency and fuel consumption exhibit relatively higher weights, reflecting their strong influence on dispatcher-optimized flight routing in line with previous studies (e.g., ICAO, 2022; Schäfer et al., 2021). By contrast, social and regulatory dimensions received comparatively lower weights, consistent with their indirect but still relevant impact on sustainability in aviation operations. Large weight values can thus be interpreted as indicators of criteria with immediate and quantifiable impacts, whereas smaller values highlight more qualitative or longer-term considerations. When compared with previously published weighting results in the literature, the distribution aligns well with earlier findings that also emphasized environmental and operational factors as dominant, while assigning smaller but non-negligible importance to softer social and regulatory dimensions. This consistency supports the robustness of the weighting approach applied in this study.

Strategic Implications of FBWM Results

- The strong prioritization of fuel consumption and emissions reflects direct alignment with global net-zero policies (IATA, 2021).
- Dispatchers and flight planners recognize that operational safety remains a binding constraint, which must be preserved while pursuing environmental objectives.
- The relatively lower emphasis on passenger-centric and scheduling comfort factors reflects that dispatcher routing optimization is predominantly driven by technical and sustainability priorities rather than purely customer service considerations.
- The weight structure validates the suitability of using Fuzzy MARCOS as the subsequent ranking model since criteria importance is now quantitatively established and will directly influence final routing alternative scores.

4.2 Fuzzy MARCOS Evaluation Results

The second stage of the analysis involved evaluating the dispatcher routing alternatives using the Fuzzy MARCOS method, applying the previously determined FBWM-derived criteria weights (see Table 3). The evaluation incorporated expert assessments for five dispatcher routing alternatives across seven sustainability-related criteria, using the linguistic scales and triangular fuzzy numbers defined in Appendix D.

Step 1: Aggregation of Expert Judgments

The linguistic evaluations provided by the 11 experts for each alternative and criterion were first aggregated by applying the fuzzy averaging technique. This aggregation process ensured the consistency and robustness of expert opinions while capturing the inherent uncertainty in qualitative assessments. Table 4 outlines the five dispatcher routing alternatives that were assessed in this study. These alternatives represent different operational strategies that dispatchers may employ to optimize flight trajectories under varying sustainability and efficiency considerations. It is important to note that the 'Direct Routing in Free Route Airspace (FRA)' alternative is inherently more complex than the other dispatcher-driven routing options. While it maximizes efficiency by allowing aircraft to select more direct trajectories across national airspace boundaries, its implementation requires significant upgrades in air traffic management systems, enhanced cross-border coordination, and higher dispatcher workload during the planning stage. Compared to conventional structured route networks or partial dispatcher optimizations, FRA involves higher cost and time demands due to the need for harmonized procedures and real-time monitoring capabilities. According to Eurocontrol's current roadmap, full-scale FRA implementation across Europe is expected to continue progressively through the mid-2020s, with broader global adoption anticipated in the following decade. Therefore, while FRA represents the most promising alternative in terms of sustainability gains, its operational complexity and resource requirements must also be acknowledged

Step 2: Normalization

Following Equation (B1) in Appendix B, fuzzy normalization was performed for each element of the decision matrix, considering whether each criterion was of benefit or cost type. In this study, all criteria were modeled as benefit criteria, thereby applying the normalization as:

$$\tilde{N}_{ij} = \frac{\tilde{x}_{ij}}{\tilde{X}_j^*} \qquad (1)$$

where $\tilde{X}_j^*$ represents the fuzzy maximum value of criterion j.

Step 3: Applying Weights to the Normalized Matrix

The normalized fuzzy values were then multiplied by their corresponding FBWM-derived weights (from Table 3), as defined in Equation (B2). This produced the weighted normalized fuzzy decision matrix.

Table 4. Aggregated Fuzzy Ratings

Criteria (C)	A1 - Standard Pre-Filed Routing	A2- Dispatcher Optimized Fuel-Saving Routing	A3- Dynamic Weather-Adaptive Routing	A4- Collaborative ATM-Integrated Routing	A5- Direct Routing in Free Route Airspace (FRA)
1	(0.50, 0.70, 0.90)	(0.80, 1.00, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)
2	(0.50, 0.70, 0.90)	(0.80, 1.00, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)
3	(0.70, 0.90, 1.00)	(0.70, 0.90, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)
4	(0.50, 0.70, 0.90)	(0.70, 0.90, 1.00)	(0.90, 1.00, 1.00)	(0.80, 1.00, 1.00)	(0.90, 1.00, 1.00)
5	(0.50, 0.70, 0.90)	(0.70, 0.90, 1.00)	(0.90, 1.00, 1.00)	(0.80, 1.00, 1.00)	(0.90, 1.00, 1.00)
6	(0.50, 0.70, 0.90)	(0.70, 0.90, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)
7	(0.50, 0.70, 0.90)	(0.70, 0.90, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)	(0.90, 1.00, 1.00)

Step 4: Determination of Ideal and Anti-Ideal Solutions

The fuzzy ideal solution (S*) and anti-ideal solution (S-) were determined according to Equations (B3) and (B4), representing the optimal and worst performances across all alternatives.

Step 5: Calculation of Utility Degrees and Final Scores

The relative utility degree K_i of each alternative was calculated using Equation (B5), incorporating both the ideal and anti-ideal reference points. Finally, the alternatives were ranked based on their defuzzified utility scores. Scores are given in Table 5.

The MARCOS results indicate that Direct Routing in Free Route Airspace (A5) received the highest overall performance score (0.913), emerging as the most preferred dispatcher routing strategy under sustainability criteria. Both Dynamic Weather-Adaptive Routing (A3) and Collaborative ATM-Integrated Routing (A4) closely followed, reflecting their strong sustainability performance, particularly in fuel consumption and emissions reduction, while ensuring safety and operational compatibility. Interestingly, while Dispatcher Optimized Fuel-Saving Routing (A2) also performed well (ranked 3rd), the conventional Standard Pre-Filed Routing (A1) consistently exhibited lower scores across most criteria, highlighting its limited contribution to decarbonization targets.

Table 5. Fuzzy MARCOS Final Utility Scores and Rankings

Alternative	K_i (Defuzzified Score)	Rank
A1 – Standard Pre-Filed Routing	0.622	5
A2 – Dispatcher Optimized Fuel-Saving Routing	0.796	3
A3 – Dynamic Weather-Adaptive Routing	0.894	2
A4 – Collaborative ATM-Integrated Routing	0.891	2
A5 – Direct Routing in Free Route Airspace (FRA)	0.913	1

4.3 Sensitivity Analysis

To examine the robustness and validity of the hybrid fuzzy MCDM framework, a sensitivity analysis was conducted focusing on the most influential criterion: C1 – Fuel Consumption Reduction. As this factor is critically important for both operational efficiency and environmental sustainability, its relative weight was increased by 10% to assess the impact on alternative rankings. All other weights were proportionally normalized to maintain consistency with the fuzzy MARCOS calculation framework. Following the adjustment, recalculated weights for each criterion are shown in Table 6.

With the adjusted weights, the fuzzy MARCOS method was reapplied to compute updated utility scores for all dispatcher route options. Table 7 displays the results of the comparative analysis. The results demonstrate that a 10% increase in the weight of fuel consumption reduction resulted in marginal shifts in the utility scores across all alternatives. The changes remained within a narrow band (maximum deviation of 0.004 in absolute utility score), and most importantly, the rank order of alternatives remained stable. The Free Route Airspace (A5) continued to rank as the most preferred routing strategy, followed by Weather-Adaptive Routing (A3) and Collaborative ATM-Integrated Routing (A4). Dispatcher Fuel-Saving Routing (A2) and Standard Pre-Filed Routing (A1) consistently occupied lower rankings. The findings confirm that while expert opinions on weighting are important, the model provides consistent decision support even under moderate variations in subjective preferences. Thus, the analytical framework is well-suited for strategic evaluation of dispatcher routing alternatives in sustainability-focused aviation operations.

Table 6. Adjusted FBWM Weights After Sensitivity Modification

Criterion	Code	Original Weight	Adjusted Weight (+10% C1)
Fuel Consumption Reduction	C1	0.228	0.245
CO_2 Emissions Reduction	C2	0.203	0.198
Flight Safety and Risk Mitigation	C3	0.162	0.158
Operational Cost Efficiency	C4	0.135	0.132
Flight Time Optimization	C5	0.112	0.109
ATM Compatibility	C6	0.089	0.087
Passenger Comfort & Scheduling Reliability	C7	0.071	0.069

Table 7. Sensitivity Analysis Results: Utility Scores Before and After Adjustment

Alternative	Baseline K_i	Adjusted K_i (+10% C1 Weight)
A1: Standard Pre-Filed Routing	0.622	0.624
A2: Dispatcher Optimized Fuel-Saving Routing	0.796	0.802
A3: Dynamic Weather-Adaptive Routing	0.894	0.898
A4: Collaborative ATM-Integrated Routing	0.891	0.895
A5: Free Route Airspace (FRA)	0.913	0.917

5. Discussion

Using the hybrid FBWM–Fuzzy MARCOS framework, Direct Routing in FRA (A5) ranked highest, followed by Dynamic Weather-Adaptive Routing (A3) and Collaborative ATM-Integrated Routing (A4); Standard Pre-Filed (A1) and Dispatcher Fuel-Saving (A2) scored lower. This ordering is consistent with evidence that trajectory-based and weather-adaptive operations deliver the largest fuel and CO_2 benefits (Álvarez & De Oliveira, 2025; Nechesa, 2023; SESAR Joint Undertaking, 2024; Calvet, 2024; Ekici et al., 2024; Zou et al., 2025) and aligns with projected sector-level savings (SESAR JU cumulative CO_2 reductions to 2050; McKinsey, 2023).

Realizing these gains depends on infrastructure and coordination: ADS-B/PBN coverage, decision-support, conflict-resolution tools, and ATM modernization (Goncharenko et al., 2021; Bertelli Fogaça et al., 2022; Rosenow et al., 2021; Frias et al., 2024). Ongoing SESAR and NextGen roll-outs strengthen feasibility (SESAR JU, 2024; FAA, 2022). Operational optimization provides near-term, low-cost abatement and bridges to medium-/long-term technologies such as SAF, hydrogen, and electrification (Jiang et al., 2024; IATA, 2025; FAA, 2021; GreenAir News, 2023; Valdés & Comendador, 2025).

Managerial and policy implications follow directly: invest in dispatcher training, advanced flight-planning/AI decision-support, and cross-border ATM coordination to exploit FRA and adaptive routing (Álvarez & De Oliveira, 2025; Rosenow et al., 2021; Goncharenko et al., 2021; Nechesa, 2023). Regulators can accelerate uptake by recognizing dynamic routing in ETS/offset frameworks, slot allocation, and congestion policies (SESAR JU, 2024; McKinsey, 2023; Valdés & Comendador, 2025).

Methodologically, the model's sensitivity robustness supports its use as a decision aid and extends MCDM applications beyond fleet, disruption, and SAF supply chain studies to the dispatcher's role in sustainability (Markatos et al., 2023; Alharasees & Kale, 2024; Seker, 2025; Lee et al., 2018; Uzgör et al., 2024; Chai & Zhou, 2022; Qasem et al., 2024; Khalifa et al., 2024; Avogadro & Redondi, 2024; NASA, 2024; GreenAir News, 2024; European Commission, 2024; IATA, 2025).

6. Conclusion

This study applied a hybrid fuzzy multi-criteria decision-making (MCDM) framework, integrating the Fuzzy Best-Worst Method (FBWM) and Fuzzy MARCOS, to evaluate dispatcher routing alternatives in the context of aviation sustainability. Drawing on expert input from eleven practitioners with backgrounds in dispatch, piloting, fuel management, and airline operations, the analysis identified Direct Routing in Free Route Airspace (FRA) and Dynamic Weather-Adaptive Routing as the most effective alternatives for reducing fuel consumption, CO_2 emissions, and flight times, while maintaining operational safety. The findings highlight how dispatcher-level decisions, often overlooked in sustainability models, directly influence environmental outcomes and operational efficiency.

The study contributes methodologically by demonstrating the usefulness of a hybrid FBWM–Fuzzy MARCOS framework in handling complex trade-offs within operational planning. It provides a replicable decision-support model that can be adapted to other areas of aviation operations management where sustainability and efficiency must be balanced.

From a practical perspective, the results point to the importance of adopting advanced dispatch tools, investing in real-time optimization technologies, and enhancing coordination with air traffic management systems. By integrating these elements, airlines and regulators can support more efficient routing practices and accelerate progress toward sector-wide sustainability goals.

Finally, while the model proved robust under sensitivity analysis, the study is limited by its regional expert base and reliance on static input data. Future research should expand the expert pool, integrate dynamic operational data, and broaden the framework to include additional dimensions such as contrail avoidance, passenger satisfaction, and airport capacity. Overall, dispatcher-driven optimization emerges as a cost-effective and immediately actionable pathway that complements long-term strategies for achieving net-zero emissions in aviation.

CRediT Author Statement

The author is solely responsible for all aspects of the study, including the conceptual design, data collection, analysis, writing, and critical revision of the manuscript.

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Appendices

Appendix A. Fuzzy Best-Worst Method (FBWM) Formulations

This appendix outlines the mathematical structure and reasoning behind the Fuzzy Best-Worst Method (FBWM) applied in this study to determine the relative importance of evaluation criteria for dispatcher routing decisions. As an extension of the classical Best-Worst Method, FBWM incorporates fuzzy set theory to address uncertainty and subjectivity in expert judgments by using triangular fuzzy numbers (TFNs). Experts identify the most and least important criteria, then provide pairwise comparisons using linguistic terms, which are systematically converted into fuzzy values. These inputs are used to formulate an optimization model that derives the fuzzy weights of each criterion while minimizing inconsistency in the comparison process. The resulting fuzzy weights are then defuzzified to yield crisp priority scores, and a consistency ratio is calculated to verify the reliability of expert evaluations. By integrating cognitive efficiency with fuzzy logic, FBWM ensures a robust, structured, and interpretable weighting process suited for complex, multi-criteria decision environments in aviation sustainability.

A.1. Linguistic Scale and Triangular Fuzzy Numbers

Linguistic pairwise comparisons provided by experts are converted into triangular fuzzy numbers (TFNs). The linguistic scale is given Table A1.

Table A1. Linguistic Scale and Triangular Fuzzy Numbers

Linguistic Term	TFN Representation
Equally Important (EI)	(1, 1, 1)
Weakly More Important (WMI)	(2, 3, 4)
Moderately More Important (MMI)	(4, 5, 6)
Strongly More Important (SMI)	(6, 7, 8)
Very Strongly More Important (VSMI)	(8, 9, 10)

A.2. FBWM Formulation

The set of decision criteria is denoted by $\mathrm{C} = \{\mathrm{c}_1, \mathrm{c}_2, \dots, \mathrm{c}_\mathrm{n}\}$, where each element c_1 represents an individual criterion considered in the evaluation process.

Step 1: Identification of Best and Worst Criteria

The decision-maker identifies:

- Best criterion: $c_B \in C$
- Worst criterion: $c_W \in C$

Step 2: Fuzzy Best-to-Others Vector

The fuzzy preference of the best criterion over all other criteria is expressed as:

$$\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \dots, \tilde{a}_{Bn}) \tag{A1}$$

where $\tilde{a}_{Bj}$ is a triangular fuzzy number representing the preference of c_B over c_j.

Step 3: Fuzzy Others-to-Worst Vector

The fuzzy preference of all criteria over the worst criterion is expressed as:

$$\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \dots, \tilde{a}_{nW}) \tag{A2}$$

where $\tilde{a}_{jW}$ is a triangular fuzzy number representing the preference of c_j over c_W.

Step 4: Fuzzy Optimization Model

The fuzzy optimization problem is formulated as:

$$\min_{\tilde{w}_j, \xi} \xi \tag{A3}$$

subject to:

$$\begin{aligned} &\left|\frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{a}_{Bj}\right| \le \xi, \forall j \\ &\left|\frac{\tilde{w}_j}{\tilde{w}_W} - \tilde{a}_{jW}\right| \le \xi, \forall j \\ &\textstyle\sum_{j=1}^{n} \tilde{w}_j = 1, \tilde{w}_j \ge 0, \forall j \end{aligned} \tag{A4}$$

A.3. Defuzzification

After solving the fuzzy optimization model, the fuzzy weights $\tilde{w}_j = (l_j, m_j, u_j)$ are defuzzified using the Center of Gravity (COG) method:

$$w_j = \frac{l_j + m_j + u_j}{3} \tag{A5}$$

where w_j is the crisp weight of criterion c_j.

A.4. Consistency Ratio of FBWM

The consistency of expert judgments is evaluated using the Fuzzy Consistency Ratio (FCR), calculated as:

$$\mathrm{FCR} = \frac{\xi^*}{\xi_{\max}} \tag{A6}$$

where ξ^* is the optimal value obtained from the optimization problem, and $\xi_{\max}$ is a predetermined maximum acceptable inconsistency value. A lower FCR indicates higher consistency in expert judgments.

Appendix B. Fuzzy MARCOS Method Formulations

The Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) method is an advanced multi-criteria decision-making (MCDM) model that enables ranking of alternatives by evaluating their proximity to both ideal and anti-ideal solutions. In this study, MARCOS is extended with fuzzy logic to handle uncertainties in expert evaluations and operational data.

B.1. Fuzzy Decision Matrix

Let there be:

- m alternatives $A = \{A_1, A_2, \ldots, A_m\}$,
- n criteria $C = \{C_1, C_2, \ldots, C_n\}$.

The fuzzy decision matrix is constructed as:

$$\tilde{X} = [\tilde{x}_{ij}]_{m\times n} \tag{B1}$$

where $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is the triangular fuzzy evaluation of alternative A_i with respect to criterion C_j.

B.2. Determination of Ideal and Anti-Ideal Solutions

The ideal $\tilde{X}^+$and anti-ideal $\tilde{X}^-$solutions are calculated as:

- For beneficial criteria:

$$\begin{aligned} \tilde{X}_j^+ &= \max_i(u_{ij}) \\ \tilde{X}_j^- &= \min_i(l_{ij}) \end{aligned} \tag{B2}$$

- For cost (non-beneficial) criteria:

$$\begin{aligned} \tilde{X}_j^+ &= \min_i(l_{ij}) \\ \tilde{X}_j^- &= \max_i(u_{ij}) \end{aligned} \tag{B3}$$

B.3. Normalization of the Decision Matrix

The fuzzy normalized matrix $\tilde{N} = [\tilde{n}_{ij}]$ is calculated as:

- For beneficial criteria:

$$\tilde{n}_{ij} = \frac{\tilde{x}_{ij}}{\tilde{x}_j^+} \tag{B4}$$

- For cost criteria:

$$\tilde{n}_{ij} = \frac{\tilde{x}_j^-}{\tilde{x}_{ij}} \tag{B5}$$

B.4. Weighted Normalized Decision Matrix

The weighted normalized matrix is obtained by multiplying normalized values with the fuzzy weights $\tilde{w}_j$ obtained from FBWM:

$$\tilde{v}_{ij} = \tilde{n}_{ij} \times \tilde{w}_j \tag{B6}$$

B.5. Utility Degree Calculation

The sum of weighted normalized values for each alternative is:

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{v}_{ij} \tag{B7}$$

Then, the utility degrees are calculated for each alternative relative to both ideal and anti-ideal solutions:

$$\begin{aligned} K_i^+ &= \frac{\tilde{S}_i}{\tilde{S}^+} \\ K_i^- &= \frac{\tilde{S}_i}{\tilde{S}^-} \end{aligned} \tag{B8}$$

where:

$$\begin{aligned} \tilde{S}^+ &= \sum_{j=1}^{n} (\tilde{w}_j \times \tilde{X}_j^+) \\ \tilde{S}^- &= \sum_{j=1}^{n} (\tilde{w}_j \times \tilde{X}_j^-) \end{aligned} \tag{B9}$$

B.6. Defuzzification

The fuzzy results are defuzzified using the Center of Gravity (COG) method:

$$K_i = \frac{l_i + m_i + u_i}{3} \tag{B10}$$

where l_i, m_i, and u_i are the lower, middle, and upper bounds of the fuzzy number $\tilde{K}_i$.

B.7. Ranking of Alternatives

Finally, the alternatives are ranked based on the defuzzified utility degree K_i. A higher K_i value indicates a more preferable alternative.

Appendix C. Sensitivity Analysis Procedure

Sensitivity analysis is employed to test the robustness and stability of the ranking results derived from the hybrid FBWM-MARCOS model. This allows the evaluation of how changes in input parameters, primarily the criteria weights, affect the final rankings of the dispatcher routing alternatives.

C.1. Purpose of Sensitivity Analysis

The primary objectives of conducting sensitivity analysis are:

- To assess the stability of the obtained rankings under weight variations.
- To identify critical criteria that have a significant impact on the ranking outcomes.
- To validate the reliability of the decision-making process when exposed to uncertainty or expert judgment variability.

C.2. Sensitivity Analysis Framework

The sensitivity analysis follows a weight perturbation approach, where the weight of one criterion is systematically varied while proportionally adjusting the weights of the remaining criteria to maintain the total weight sum of 1.

C.3. Perturbation of Criterion Weight

Let:

- w_j denote the original normalized weight of criterion C_j.
- Δ represent the adjustment increment applied to w_j.

The perturbed weight of criterion C_j is calculated as:

$$w_j^* = w_j + \Delta. \tag{C1}$$

The weights of the remaining criteria C_{-j} are adjusted proportionally:

$$w^*_{-j} = w_{-j} \times \left(\frac{1-w_j^*}{1-w_j}\right) \quad \text{(C2)}$$

This ensures that:

$$\sum_{i=1}^{n} w_i^* = 1. \quad \text{(C3)}$$

C.4. Range of Weight Variation

Each criterion weight is varied within a feasible range:

$$\Delta \in \left[-w_j, \min\left(1 - w_j, \Delta_{\max}\right)\right] \quad \text{(C4)}$$

where $\Delta_{\max}$ is typically selected (e.g., $\pm 30\%$) to reflect practical expert judgment deviations without violating non-negativity constraints.

C.5. Recalculation of MARCOS Scores

For each perturbed weight scenario:

1. The FBWM-derived weights $\boldsymbol{w_i}$ are updated according to Equations C.1-C.3.
2. The fuzzy MARCOS model is re-applied using the updated weights to recalculate:
    - Weighted normalized matrix $\tilde{\boldsymbol{v}}_{\boldsymbol{ij}}$ (Equation B.8),
    - Utility scores $\boldsymbol{K_i}$ (Equations B.9-B.14).
3. New rankings are generated for each scenario.

C.6. Stability Measurement

For each scenario, the rank stability is assessed:

- Stable ranking: No change in the order of alternatives.
- Rank shift: Change in position of one or more alternatives.

Additionally, a sensitivity index $\boldsymbol{S_j}$ can be computed for each criterion:

$$S_j = \frac{\Delta R}{\Delta w_j} \quad \text{(C5)}$$

where:

- ΔR is the maximum observed rank change.
- Δw_j is the applied weight variation.

Higher S_j values indicate greater sensitivity to changes in that criterion.

Appendix D. Linguistic Scales

This appendix details the fuzzy linguistic variables and corresponding triangular fuzzy numbers (TFNs) employed in both the criteria weighting stage using the Fuzzy Best-Worst Method (FBWM) and the evaluation phase using the Fuzzy MARCOS approach. To ensure methodological consistency and comparability across expert inputs, the study adopts standardized linguistic scales tailored to both preference elicitation and alternative evaluation. The appendix also includes a comprehensive notation table that defines all mathematical symbols and abbreviations used throughout the analytical model, thereby enhancing transparency and replicability of the framework.

D1. Symbols, Notations, and Fuzzy Linguistic Terms

This section provides a comprehensive overview of the symbols, mathematical notations, and fuzzy linguistic terms used throughout the hybrid fuzzy MCDM framework integrating the FBWM and Fuzzy MARCOS methods. The notations define key elements such as criteria weights, fuzzy decision matrix components, ideal and anti-ideal solutions, normalization equations, and utility functions. Each symbol is listed alongside a brief description to facilitate clarity in the mathematical modeling process. Additionally, this section outlines the linguistic terms used by experts during pairwise comparisons and alternative evaluations, along with their corresponding Triangular Fuzzy Numbers (TFNs). These fuzzy linguistic terms ensure that subjective expert judgments are systematically converted into quantitative values, enabling consistent analysis under uncertainty. Together, the standardized symbols and linguistic scales serve as the foundational language of the model, ensuring transparency, interpretability, and replicability of the decision-making process. Table D1 outlines the key notations and associated linguistic scales.

D.2. Linguistic Scales for Expert Evaluation

For both FBWM and MARCOS assessments, experts provided linguistic evaluations converted into triangular fuzzy numbers (TFNs). The adopted scale is presented in Table D2.

Table D1. Notation Table and Linguistic Scales

Notation	Description
A_i	The i^{th} alternative (dispatcher routing option)
C_j	The j^{th} criterion
m	Total number of alternatives
n	Total number of criteria
$\tilde{x}_{ij}$	Fuzzy evaluation of alternative A_i with respect to criterion C_j, expressed as triangular fuzzy number (TFN): (l_{ij}, m_{ij}, u_{ij})
$\tilde{X}$	Fuzzy decision matrix
$\tilde{X}^+, \tilde{X}^-$	Fuzzy ideal and anti-ideal solutions
$\tilde{n}_{ij}$	Normalized fuzzy value for alternative Ai under criterion Cj
$\tilde{w}_j$	Fuzzy weight of criterion Cj, derived from FBWM
$\tilde{v}_{ij}$	Weighted normalized fuzzy value for alternative Ai under criterion Cj
$\tilde{S}_i$	Sum of weighted normalized values for alternative Ai
$\tilde{S}^+, \tilde{S}^-$	Sum of weighted normalized ideal and anti-ideal values
K_i^+, K_i^-	Utility degree relative to ideal and anti-ideal solutions
K_i	Defuzzified utility score for alternative Ai
S_j	Sensitivity index for criterion Cj
Δ	Applied variation in criterion weight during sensitivity analysis
w_j^*	Perturbed weight of criterion Cj
w_{-j}^*	Adjusted weights for remaining criteria

Table D2. Linguistic Scale and Corresponding Triangular Fuzzy Numbers (TFNs) for Expert Judgments

Linguistic Term	TFN Representation (l, m, u)
Extremely Low (EL)	(0.00, 0.00, 0.10)
Very Low (VL)	(0.00, 0.10, 0.30)
Low (L)	(0.10, 0.30, 0.50)
Medium Low (ML)	(0.30, 0.50, 0.70)
Medium (M)	(0.50, 0.70, 0.90)
Medium High (MH)	(0.70, 0.90, 1.00)
High (H)	(0.80, 1.00, 1.00)
Very High (VH)	(0.90, 1.00, 1.00)
Extremely High (EH)	(1.00, 1.00, 1.00)

D.3. Linguistic Scales for Best-Worst Comparisons

For the FBWM pairwise comparisons between best and worst criteria, 9-level linguistic scale was applied which is illustrated in Table D3.

Table D3. Linguistic Preference Scale and Triangular Fuzzy Number (TFN) Representation for FBWM Pairwise Comparisons

Preference Level	**TFN Representation** $(\boldsymbol{l}, \boldsymbol{m}, \boldsymbol{u})$
Equal Importance	(1, 1, 1)
Weak Importance	(1, 2, 3)
Moderate Importance	(2, 3, 4)
Moderate Plus Importance	(3, 4, 5)
Strong Importance	(4, 5, 6)
Strong Plus Importance	(5, 6, 7)
Very Strong Importance	(6, 7, 8)
Very Strong Plus Importance	(7, 8, 9)
Extreme Importance	(9, 9, 9)

Note: The above linguistic scales enable both subjective flexibility and mathematical consistency, allowing expert judgments to be processed within the fuzzy MCDM framework with reduced cognitive burden and higher reliability.