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Fuzzy MCDM Methodology Application in Analysis of Annual Operational Efficiency in Passenger and Freight Air Transport

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Abstract

The airline industry plays a vital role in global mobility and international trade, which makes the evaluation of its operational efficiency an important strategic task. This study evaluates and ranks the operational performance of passenger and freight air transport in Serbia over the period 2014–2023 by employing a fuzzy multi-criteria decision-making framework. Six key performance criteria were defined, with their weighting coefficients determined using the fuzzy MEREC method, while the ranking of alternatives was conducted using the fuzzy MARCOS method. The obtained results reveal noticeable variations in performance throughout the observed period and provide insights into efficiency trends in both passenger and freight segments of air transport. Furthermore, a sensitivity analysis confirmed the robustness and stability of the ranking outcomes. The findings of this research can support evidence-based decision-making and contribute to enhancing the operational efficiency and competitiveness of the air transport sector.

Keywords: air transport; operational performance; fuzzy MEREC; fuzzy MARCOS; sensitivity analysis

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1. Introduction

The efficient organization of air transportation is a key factor in strengthening airline competitiveness within the global transport system, particularly under conditions of increasing aviation globalization [1]. The development of aviation is recognized as a strategic priority in national transport policies, ensuring passenger safety, transparency, and adaptation to dynamic economic changes.

Air transport is characterized by short travel times but also by high operating costs, significant fuel consumption, and limited capacities. While passenger transport has historically dominated, the unreliability of freight carried on passenger aircraft led to the introduction of dedicated cargo carriers [2,3]. Passenger air transport fosters global connectivity, tourism, and international cooperation [4], whereas cargo transport supports global trade in high-value, perishable, and time-sensitive goods [5]. Effective cargo operations require multimodal integration, capacity planning, and storage efficiency.

In Serbia, air transport plays a vital role in international connectivity [6]. Investments in infrastructure and the privatization of Air Serbia have strengthened its regional position, with expanded routes achieved through global partnerships. Authorities enforce ICAO (International Civil Aviation Organization) and EASA (European Union Aviation Safety Agency) standards to ensure safety, protect passenger rights, and promote sustainability. However, the sector continues to face challenges from competition, economic pressures, and the need for further infrastructure investment.

Serbia's future potential lies in expanding infrastructure, establishing new connections, and attracting international carriers [7]. Cargo air transport, though smaller in scale, has grown through targeted investments, particularly at Belgrade's Nikola Tesla Airport, which benefits from a favorable geographical position. To enhance competitiveness, further development of cargo terminals, advanced technologies, and intermodal integration with road and rail is essential. Rising e-commerce and global logistics demands also create opportunities for specialized cargo services and stronger cooperation with international logistics firms [8].

The air transport system comprises interconnected carriers, airports, and air traffic control, supported by key stakeholders including airlines, navigation service providers, airport operators, and aircraft manufacturers [9].

Following the introductory section, which addresses the significance and operational performance of air transport within the framework of multi-criteria decision-making (MCDM), the Section 2 provides a comprehensive review of the literature concerning the application of various approaches and methodologies—particularly fuzzy extensions of MCDM—for evaluating the performance of both passenger and freight air transport (Figure 1). The integration of fuzzy logic into MCDM techniques has gained prominence due to its capacity to capture uncertainty, vagueness, and imprecision inherent in expert evaluations and operational data, thereby ensuring more robust and reliable assessment outcomes.

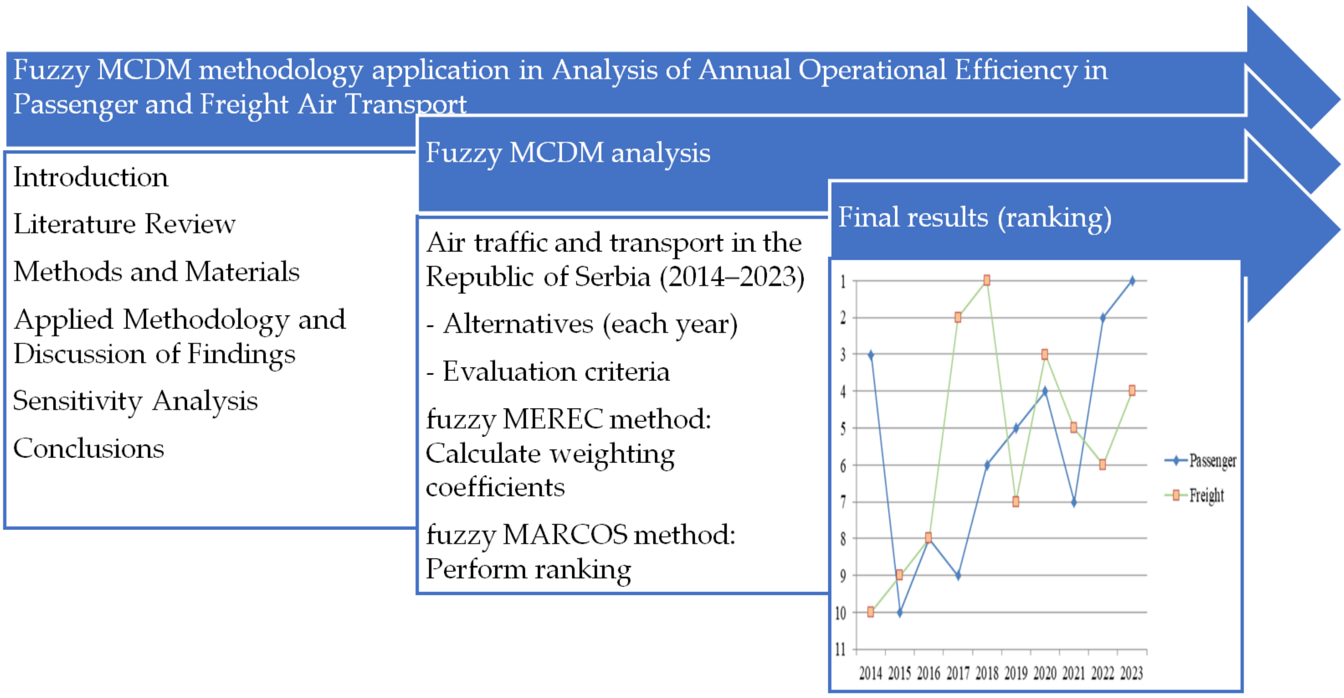

Figure 1. Overview of the Paper Structure.

A broad spectrum of criteria can be taken into account when analyzing the operational performance of air transport systems, encompassing both passenger and cargo traffic. Accordingly, the Section 3 establishes the general framework for the application of MCDM methods, with particular emphasis on fuzzy extensions, together with the definition of evaluation criteria and the structure of the input dataset. The Section 4 provides a detailed exposition of the MEREC (Method based on the Removal Effects of Criteria) procedure, applied for the determination of the weighting coefficients of the evaluation criteria. These coefficients, expressed through fuzzy values to account for uncertainty and variability in the data, were subsequently incorporated into the MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) method in order to rank the operational performance of passenger and freight air transport in the Republic of Serbia for each year within the 2014–2023 periods. Each year was treated as a distinct alternative, and the analysis relied on relevant, officially available statistical data. In addition, in the Section 5 a sensitivity analysis was conducted to verify the robustness of the obtained weighting coefficients, thereby confirming the stability of the results. Finally, the Section 6 synthesizes the principal research findings and outlines recommendations and directions for future investigations.

Air transport represents a key component of modern logistics and transportation systems, and the operational efficiency of airlines significantly influences economic connectivity, competitiveness, and sustainable development. In conditions of fluctuating demand, rising operational costs, technological advancements, and global disruptions (e.g., the COVID-19 pandemic), it becomes essential to develop reliable methods for objectively measuring and comparing air transport performance over extended periods. However, existing literature and practice reveal a limited number of studies that jointly analyze the operational efficiency of both passenger and cargo air transport using fuzzy (MCDM) methodologies. This research gap constitutes the primary motivation for conducting this study.

The main novelties and contributions of this research can be summarized as follows:

- Simultaneous evaluation of passenger and freight air transport within a unified decision-making framework, which is rarely addressed in existing literature.
- Application of the fuzzy MEREC method to objectively determine criterion weights based on the influence of each criterion on the overall decision-making process.
- Use of the fuzzy MARCOS method for ranking performance across the observed time span, enabling the assessment of efficiency dynamics.
- Introduction of time as an alternative, where each year is treated as a unique alternative, allowing continuous monitoring of efficiency trends over a ten-year period.
- Implementation of sensitivity analysis to confirm the robustness and stability of the obtained results.
- Use of real operational data from the air transport sector of the Republic of Serbia (2014–2023), ensuring high practical relevance and providing a basis for strategic planning and decision-making.

2. Literature Review

In the contemporary interconnected environment, the airline industry assumes a pivotal role in facilitating the rapid and efficient global movement of both passengers and goods. Confronted with intensifying competition, airlines are compelled to continuously enhance their operations in order to secure a sustainable competitive advantage. The operational performance of the airline sector is shaped by a wide array of determinants, encompassing both short-term and long-term strategic planning, fleet and crew management, safety, reliability, cost efficiency, customer satisfaction, and environmental sustainability.

To stress the importance of the airline industry, different studies were conducted [10]. The causal relationship between air transport and economic growth in the ten countries with the highest air transport volumes from 1970 to 2021, employing bootstrap Toda–Yamamoto and Fourier Toda–Yamamoto causality tests, was a problem of interest [10]. The results reveal a unidirectional causal link from air transport to economic growth in most countries, except Russia and Brazil, while bidirectional relationships are observed between air freight and growth in Japan, and between registered departures and growth in China. The findings suggest that Fourier-based tests provide more consistent results and highlight the importance of considering multiple dimensions of air transport to capture its overall economic impact [10].

Airlines encounter numerous challenges related to optimization and decision-making, which necessitate the adoption of a comprehensive decision-making framework capable of integrating all relevant factors and providing effective solutions for performance improvement [11]. In recent years, the sector has increasingly embraced MCDM methodologies [12–16] as a means of addressing complex managerial problems characterized by multiple and often conflicting objectives. These approaches explicitly account for the interdependencies and trade-offs among diverse performance indicators, thereby enabling the evaluation and ranking of alternatives on the basis of a predefined set of criteria [17,18]. By embedding MCDM techniques within their strategic and operational processes, airlines are able to systematically assess performance outcomes and to identify targeted opportunities for operational enhancement [19,20].

The current state of the aviation industry and strategies for improving the organization of air transport within the broader economy is very interesting research topic [21]. Applying a dialectical-materialist approach and methods such as induction, deduction, and abstraction, the study draws on statistical data from both international and national sources. It identifies five key elements of global air transport, highlighting passenger traffic as the dominant activity and noting the pandemic's significant impact on economic dynamics. The future of aviation is closely tied to innovation, including sustainable fuels, market expansion, and employment growth [22]. Operational efficiency is enhanced through precise scheduling, smart services, and improved safety protocols, all of which support the sustainable development of the industry.

A paradigm shift has emerged, emphasizing the alignment of outcomes with the preferences of the Decision Maker (DM), thereby prioritizing satisfactory solutions over strictly optimal ones. Decision problems are generally classified into four categories: selection, ranking, sorting, and elimination. Nevertheless, inaccuracies in both quantitative and qualitative data often undermine the reliability of MCDM applications, particularly in cases where linguistic assessments are transformed into numerical representations, which inevitably introduces uncertainty. Moreover, numerous methods are subject to the Rank Reversal Phenomenon (RRP), whereby the ranking of alternatives changes following the addition or removal of options, in contradiction to the principle of independence of alternatives.

A variety of problems in airline industry is being solved by applying MCDM techniques for analysis and improvement. The research [23] employs MCDM techniques to improve the ground operations of low-cost carriers (LCCs). Using fuzzy AHP and fuzzy TOPSIS, a case study of three Turkish airlines evaluates performance across five criteria and eighteen sub-criteria. The results indicate that the third airline performs best, providing insights into operational strategies and performance improvement in the LCC sector. The study also outlines limitations and offers directions for future research [23]. The Fuzzy TOPSIS methodology was used to prioritize risk mitigation strategies in air cargo operations, which face risks such as inefficiencies, cyber threats, regulatory challenges, and environmental concerns [24]. A structured framework combining expert judgment with fuzzy logic was developed to evaluate ten criteria, including cost-effectiveness, efficiency, and scalability. The results indicate that Enhanced Data Security Measures ranked highest, underscoring the importance of cyber security, while Resilience Building and Safety Protocols also proved critical. The study demonstrates the value of Fuzzy TOPSIS in addressing uncertainty in risk assessment and provides practical insights for improving risk management in air cargo, with future research directed toward dynamic assessment and complementary MCDM methods [24].

Service quality is recognized as a key corporate strategy for gaining a competitive advantage. With the growing demand for air transport, airports have become essential hubs, bringing airport service quality into focus. As gateways connecting cities to the world, the quality of service at airports is assessed based on how well it meets passenger expectations. This study [25] aims to evaluate service quality by analyzing 17 airports that were rated as five-star airports by Skytrax in 2021, using 11 criteria. The MEREC method was used to determine the significance of each criterion, while MARCOS and CoCoSo methods were applied to rank the airports based on service quality. The criteria used for evaluation include transportation services, security screenings, immigration services, signage, arrival services, departure services, transfer passenger services, terminal comfort, terminal facilities, shopping options, and food and beverage services. The analysis using the MEREC method identified immigration services as the most influential factor in determining airport service quality. Based on the combined results of MARCOS and CoCoSo methods, Chubu Centrair Airport ranked highest for service quality, while Tokyo Haneda Airport ranked lowest [25].

Classical approaches such as AHP (Analytic Hierarchy Process), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations), and ELECTRE (ELimination Et Choix Traduisant la REalité) remain widely employed, although they exhibit certain methodological limitations [26–30]. These shortcomings have stimulated the development of more advanced methodologies, including MARCOS, CoCoSo, and RAWEC, specifically designed to mitigate such challenges [31–34]. Among these, the MARCOS method has demonstrated considerable applicability across a variety of engineering and industrial contexts due to its conceptual simplicity and robustness. Furthermore, MARCOS is frequently combined with complementary techniques such as SWARA (Step-wise Weight Assessment Ratio Analysis) or AHP, thereby enhancing its methodological flexibility and practical relevance. The research [35] aims to analyze the factors that influence and determine the overall workload of transport operators (drivers and pilots) while comparing the key elements of both systems. To establish a general hierarchical model, the AHP is applied. In this study, the Saaty Scale is used for scoring, enabling the representation of missing data through matrices that can be calculated using a specific method [35].

In recent studies, fuzzy extensions of MARCOS have also been increasingly adopted, as they provide an effective means of addressing uncertainty, vagueness, and imprecision in expert evaluations, further strengthening the robustness of decision-making outcomes.

Numerous studies in the literature have examined the measurement of operational efficiency; however, this research area, particularly in the context of passenger and cargo air transport, remains insufficiently explored. The present study evaluates calendar years as alternatives against a defined set of criteria for the operational performance of passenger and cargo air transport in the Republic of Serbia by employing MCDM techniques. In order to account for uncertainty and imprecision in the data, fuzzy extensions of MCDM are integrated into the analysis, thereby enhancing the robustness and reliability of the obtained results.

3. Methods and Materials

Operational efficiency is one of the key indicators of success in the air transport sector. In light of modern challenges such as rising fuel costs, increased competition, strict environmental standards, and high user expectations, it is essential to continuously enhance the operational performance of airlines and airport operators. Operational efficiency is reflected in the system's ability to optimally utilize available resources (human, material, technological) while minimizing costs, time, and negative impact on the environment, and ensuring a high level of service and security [36].

The process of improving operational efficiency therefore requires making numerous strategic, tactical, and operational decisions. Since such decisions are influenced by different criteria, including financial indicators, environmental standards, safety, user satisfaction, and regulatory requirements, harmonizing these often conflicting factors becomes a considerable challenge. Multi-criteria methods and DEA (Data Envelopment Analysis) [37] provide a structured framework for analyzing alternatives and selecting optimal strategies. Managing complex operations in air transport thus involves decision-making processes that encompass a wide range of interdependent factors. In this regard, MCDM emerges as an indispensable tool for managers and decision-makers. Moreover, given that decision-making environments are frequently characterized by uncertainty, subjectivity, and vagueness, fuzzy extensions of MCDM methods are increasingly applied [38–40]. By incorporating fuzzy numbers into the evaluation process, these methods allow for a more realistic representation of imprecise judgments and incomplete data, thereby enabling more robust and reliable assessments of alternatives [41,42].

3.1. Fuzzy MEREC Method

In MCDM tasks, the determination of criteria weights is of paramount importance, as they exert a considerable influence on the final outcomes. Consequently, a variety of techniques have been developed to evaluate these weights, which are generally classified as subjective, objective, or hybrid in nature. In this study, an objective weighting approach, namely MEREC, is employed [43]. This method introduces a novel concept by deriving weights from the impact of each criterion's removal on the overall performance of the alternatives [44].

The originality of MEREC method lies in its focus on assessing how the exclusion of a given criterion alters the aggregate performance of alternatives, thereby distinguishing it from conventional techniques that rely predominantly on variations in magnitude. This perspective not only facilitates the assignment of more representative weights but also assists decision-makers in identifying criteria that may be redundant. By emphasizing causality and allowing for the incorporation of different aggregation functions, MEREC provides additional flexibility. In this research, fuzzy extensions are integrated into the MEREC framework to more effectively capture uncertainty, vagueness, and imprecision in the evaluation process [45,46]. The development of innovative MCDM methodologies from alternative viewpoints enhances the robustness of decision-making processes, particularly when such approaches are combined with other established methods. Although simulation results indicate that MEREC's correlation with traditional weighting techniques diminishes with increasing problem complexity, this limitation is widely acknowledged in MCDM research and reinforces the need for methodological integration to ensure reliable and stable outcomes [47,48].

To account for uncertainty and imprecision in the evaluation process, triangular fuzzy numbers (TFNs) were employed to fuzzify the entries of the initial decision matrix [49,50]. Each TFN is expressed in the form $x_{ij} = (l_{ij}, m_{ij}, u_{ij})$, where l_{ij} denotes the lower bound,

m_{ij} the most likely value, and u_{ij} the upper bound, with the condition $l_{ij} \leq m_{ij} \leq u_{ij}$), if its membership function is equal to:

$$\mu_M(x) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l \leq x \leq m \\ 1, & x = m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & x > u \end{cases} \tag{1}$$

Step 1: Creating a decision matrix

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{2}$$

where x_{ij} is the value of alternative i according to criterion j.

Step 2: Decision matrix normalization

The values in the decision matrix are normalized depending on the type of criteria:

- maximizing criteria (beneficial criteria):

$$r_{ij} = \frac{\min \mathrm{x}_{ij}}{x_{ij}} \approx \left(\frac{l_j^{min}}{u_{ij}}, \frac{m_j^{min}}{m_{ij}}, \frac{u_j^{min}}{l_{ij}} \right) \tag{3}$$

where $l_j^{min}, m_j^{min}, and\ u_j^{min}$ are the minimum values of the corresponding fuzzy triplets for criterion j.

- minimizing criteria (non-beneficial criteria):

$$r_{ij} = \frac{\mathrm{x}_{ij}}{\mathrm{max} x_{ij}} \approx \left(\frac{l_{ij}}{u_j^{max}}, \frac{m_{ij}}{m_j^{max}}, \frac{u_{ij}}{l_j^{max}} \right) \tag{4}$$

where $u_j^{max}, m_j^{max}, and\ l_j^{max}$ are the maximum values of the corresponding fuzzy triplets for criterion j.

Step 3: The overall performance of the alternatives is assessed as follows:

$$\begin{gathered} S_i = \ln\left(1 + \left(\frac{1}{m}\sum_j |ln(r_{ij})|\right)\right) \\ S_i = \left(\ln\left(1 + \frac{1}{m}\sum_j -\ln u_{ij}\right), \ln\left(1 + \frac{1}{m}\sum_j -\ln m_{ij}\right), \ln\left(1 + \frac{1}{m}\sum_j -\ln l_{ij}\right)\right) \end{gathered} \tag{5}$$

Step 4: Evaluate the performance of the alternatives by excluding each criterion as follows:

$$\begin{gathered} \mathrm{S}'_{ij} = \ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j} |ln(r_{ik})|\right)\right) \\ \mathrm{S}'_{ij} = \left(\ln\left(1 + \frac{1}{m}\sum_{k\neq j} -\ln u_{ik}\right), \ln\left(1 + \frac{1}{m}\sum_{k\neq j} -\ln m_{ik}\right), \ln\left(1 + \frac{1}{m}\sum_{k\neq j} -\ln l_{ik}\right)\right) \end{gathered} \tag{6}$$

Step 5: The summation of absolute deviations is computed in this step. Specifically, the impact of excluding the *j*-th criterion is evaluated based on the results obtained in Steps 3 and 4. Let E_j denote the removal effect associated with the j-th criterion. The corresponding values of E_j are determined using the following formula:

$$\mathrm{E}_j = \sum_i \left| \mathrm{S}'_{ij} - S_i \right| \tag{7}$$

where values S_i and S'_{ij} are defuzzificated using the following expression:

$$centroid_a = \frac{\mathrm{l}_a + \mathrm{m}_a + \mathrm{u}_a}{3} \tag{8}$$

Step 6: Calculate the final weights of the criteria. In this phase, the objective weight of each criterion is determined based on the removal effects E_j calculated in Step 5.

$$\mathrm{w}_j = \frac{\mathrm{E}_j}{\sum_k \mathrm{E}_k}, \quad \sum_{j=1}^{m} w_j = 1 \tag{9}$$

3.2. Fuzzy MARCOS Method

The MARCOS method evaluates the relationship between the performance scores of the examined alternatives and two predefined reference points, namely the ideal and anti-ideal solutions. Through this comparison, the method determines the extent to which each alternative approximates the optimal (ideal) outcome while simultaneously measuring its deviation from the least desirable (anti-ideal) scenario [51].

In its fuzzy extension, the MARCOS methodology computes the utility of each alternative in the fuzzy domain: criterion values and the two reference points are modeled as triangular fuzzy numbers (TFNs), the closeness to the (fuzzy) ideal and the remoteness from the (fuzzy) anti-ideal are obtained via fuzzy arithmetic, and the resulting fuzzy utilities are defuzzified (e.g., using the centroid method) to yield crisp utility values. On this basis, fuzzy MARCOS identifies the compromise solution—i.e., the alternative that most evenly balances multiple, potentially conflicting criteria while explicitly accounting for uncertainty and imprecision in measurements and expert judgments [52,53].

The MARCOS framework thus enables objective multi-criteria ranking while consistently incorporating both extreme reference points, ensuring that each alternative is assessed across the full spectrum of potential outcomes. By representing inputs and benchmarks fuzzily and resolving them to crisp scores only at the final stage, the approach enhances robustness to noise and vagueness and improves the interpretability of trade-offs among cost, efficiency, risk, and environmental impact.

Moreover, MARCOS-both in its classical and fuzzy variants-exhibits high adaptability across domains such as engineering design, logistics optimization, strategic resource management, and transport systems. Its clear structure supports rational and transparent decision-making in complex, dynamic settings where competing objectives must be carefully balanced to achieve operational excellence.

The MARCOS method follows a structured procedure that begins with the construction of the initial decision matrix, which incorporates n criteria and m alternatives [54,55]. Once the decision matrix is formed (Step 1), the ideal and anti-ideal solutions are determined for each criterion (Step 2) using Equations (10) and (11), representing the best and worst possible values depending on whether the criterion is beneficial or non-beneficial.

$$x_{ai} = \max_j \mathrm{x}_{ij}; j \in B \tag{10}$$

$$x_{aai} = \min_j \mathrm{x}_{ij}; j \in C \tag{11}$$

The third step involves the normalization of the decision matrix, where the values are adjusted according to the type of criterion. For maximizing (beneficial) criteria, normalization is carried out as in Equation (3), whereas for minimizing (non-beneficial) criteria, normalization is expressed as in Equation (4).

In the fourth step, the normalized values are multiplied by the corresponding weights to obtain the weighted normalized matrix:

$$v_{ij} = \mathrm{w}_j \times r_{ij} \tag{12}$$

The fifth step calculates the utility degrees K_i^+ and K_i^- for each alternative, where

$$\mathrm{K_i^+} = \frac{\mathrm{S_i}}{\mathrm{S_{ai}}} \tag{13}$$

$$\mathrm{K}_i^- = \frac{\mathrm{S}_i}{S_{aai}} \tag{14}$$

and S_i denotes the sum of the weighted normalized values of the i-th alternative, while S_{ai} and S_{aai} represent the aggregate values of the ideal and anti-ideal alternatives, respectively.

In the sixth step, the utility functions relative to the ideal and anti-ideal solutions are computed:

$$\mathrm{f}\left(\mathrm{K}_i^+\right) = \frac{\mathrm{K}_i^-}{\mathrm{K}_i^+ + \mathrm{K}_i^-} \tag{15}$$

$$\mathrm{f}\left(\mathrm{K}_i^-\right) = \frac{\mathrm{K}_i^+}{\mathrm{K}_i^+ + \mathrm{K}_i^-} \tag{16}$$

The seventh step derives the overall utility function of each alternative:

$$\mathrm{f}(\mathrm{K}_i) = \frac{\mathrm{K}_i^+ + \mathrm{K}_i^-}{1 + \frac{1 - f\left(\mathrm{K}_i^+\right)}{f\left(\mathrm{K}_i^+\right)} + \frac{1 - f\left(\mathrm{K}_i^-\right)}{f\left(\mathrm{K}_i^-\right)}} \tag{17}$$

where values $\mathrm{f(K_i)}$, $\mathrm{f}\left(\mathrm{K}_i^+\right)$ and $\mathrm{f}\left(\mathrm{K}_i^-\right)$ are defuzzificated using the following expression (7).

Since fuzzy numbers are applied in the earlier stages, these utility values are subsequently defuzzified to obtain crisp values suitable for ranking. The final step ranks the alternatives based on their utility scores, with higher values indicating closer proximity to the ideal solution. The alternative with the maximum utility value is identified as the compromise solution, representing the most suitable choice.

Through this structured sequence, the MARCOS method enables decision-makers to systematically balance multiple, and often conflicting, criteria. By incorporating fuzzy extensions, the method further enhances robustness by addressing uncertainty and imprecision in the input data. Its methodological flexibility and mathematical rigor make MARCOS particularly effective in domains such as transportation planning, logistics, and resource management, where decision-making must account for complex trade-offs under dynamic conditions.

3.3. Input Data

The MCDM represents a pivotal branch of Operations Research (OR) concerned with decisions that involve the simultaneous evaluation of multiple, often conflicting, criteria. The overarching aim of OR is to enhance decision-making processes by offering mathematical models and optimization tools that support rational and well-structured choices. The MCDM draws upon a wide range of disciplines, including engineering, economics, computer science, and mathematics. The use of multi-criteria techniques enables decision-makers—such as managers and policy-makers—to actively participate in the process, thereby improving their understanding of the complexity and uncertainty of the business environment. Their role extends beyond the application of pre-existing solutions to encompass the analysis, structuring, and modeling of problems, as well as the interpretation and implementation of results. The evolution of MCDM methodologies has been largely driven by advances in information technologies and computational systems, which have significantly contributed to their growing applicability. Owing to their practical relevance, multi-criteria methods have rapidly advanced, facilitating the resolution of complex decision problems. These methods differ in terms of the quantity and quality of available information, the approaches employed the degree of complexity, and their underlying mathematical properties.

Operational efficiency in air transport entails maximizing the utilization of available resources while minimizing costs and time. Effective flight planning, fleet management, ground service coordination, and timely adaptation to fluctuations in traffic and weather conditions are critical determinants of success. The integration of advanced information technologies, process automation, and data analytics can yield substantial improvements in operational performance. Decisions derived from MCDM analyses play a crucial role in strengthening operational efficiency, as they enable the attainment of an optimal balance among the frequently conflicting objectives of cost, quality, and safety. In this regard, the incorporation of fuzzy extensions into MCDM methods provides additional robustness, as they effectively capture uncertainty, vagueness, and imprecision inherent in expert judgments and operational data, thereby ensuring more reliable and resilient decision-making outcomes.

As part of the operational performance analysis of the passenger and freight air transport sectors in the Republic of Serbia over the period 2014–2023, the input data—defined as evaluation criteria (Table 1)—were derived from regular monthly, quarterly, and annual statistical reports, the aggregated results of which are presented in Tables 2 and 3 [56].

Table 1. Air transport criteria.

No.	Criteria	Unit
C_1	Passenger kilometers	pkm, mill.
C_2	Ton-kilometers	tkm, thous.
C_3	Passengers transported	thous.
C_4	Goods carried	t, thous.
C_5	Employees in transport	number
C_6	Consumption of fuel in transport	t, thous.
C_7	Passengers traffic	thous.
C_8	Cargo traffic	t, thous.
C_9	Foreign currency receipts from transport	USD, thous.

These data are expressed through a set of criteria, including the number of passengers transported, passenger and tonne-kilometres achieved, the number of employees, fuel consumption, passenger and cargo traffic volume, and foreign currency receipts from transport services. These indicators enable a multi-criteria evaluation of air transport efficiency and performance, focusing on identifying the key factors contributing to operational effectiveness throughout the observed period.

Table 2. The initial matrix utilized for determining the performances of passenger air transport: C_1, C_3, C_5, C_6, C_7 and C_9 [56].

Alternatives (Years)	Criteria					
	C_1	C_3	C_5	C_6	C_7	C_9
	Max	Min	Min	Min	Max	Max
A_1	2454	2348	1858	105	4661	159,978
A_2	2642	2575	2601	107	4812	215,647
A_3	3008	2660	2693	119	5006	243,394
A_4	3203	2662	3163	120	5673	228,782
A_5	3004	2524	3113	112	5988	232,215
A_6	3303	2782	3974	121	6581	288,773
A_7	1214	892	2971	59	2057	243,857
A_8	1983	1564	2824	81	3295	296,282
A_9	3193	2720	3014	121	6077	416,324
A_{10}	5155	4143	3770	184	8400	478,322

Table 3. The initial matrix utilized for determining the performances of freight air transport: C_2, C_4, C_5, C_6, C_8 and C_9 [56].

Alternatives (Years)	Criteria					
	C_2	C_4	C_5	C_6	C_8	C_9
	Max	Max	Min	Min	Max	Max
A_1	3277	2785	1858	105	11,473	159,978
A_2	4660	3575	2601	107	15,385	215,647
A_3	10,246	4913	2693	119	18,000	243,394
A_4	20,752	6651	3163	120	24,384	228,782
A_5	20,165	6738	3113	112	25,316	232,215
A_6	15,056	5642	3974	121	22,602	288,773
A_7	15,720	4194	2971	59	18,272	243,857
A_8	17,151	4730	2824	81	15,083	296,282
A_9	17,749	4944	3014	121	13,639	416,324
A_{10}	21,915	5703	3770	184	15,305	478,322

4. Applied Methodology and Discussion of Findings

It should be emphasized that the solutions obtained through MCDM methods cannot be considered strictly optimal or the only acceptable outcomes. Instead, these approaches serve to provide a structured framework for analyzing complex decision problems, thereby assisting decision-makers in identifying high-quality and practically feasible solutions. Nevertheless, real-world decision-making environments are frequently characterized by uncertainty, vagueness, and incomplete information. Consequently, the application of fuzzy extensions of MCDM methods has become increasingly significant.

This approach promotes consensus-building by reducing unnecessary conflicts among stakeholders, including policymakers, the public and other interest groups. In this analysis, the alternatives—represented by the observed years—and the relevant evaluation criteria are organized within the initial decision matrices. The objective, determined based on whether each criterion has a positive or negative impact, focuses on assessing the operational performance of air transport in the Republic of Serbia.

4.1. Fuzzy MEREC Application

The subchapter formalizes and connects the entire fuzzy-MEREC procedure with the results reported in Tables 4–9. The starting point is the classical MEREC "removal-effect" logic, extended with triangular fuzzy numbers (TFNs) to capture measurement error and uncertainty. The TFNs were selected because this form of fuzzy representation is among the most widely used and computationally efficient in MCDM [57]. The TFN structure enables the expression of uncertainty using simple lower, middle, and upper bounds, which correspond to the real-world characteristics of transport and economic data that are frequently affected by fluctuations, measurement imprecision, reporting delays, or estimation error. In comparison with other fuzzy number types (e.g., trapezoidal or Gaussian), TFNs require fewer parameters, offer straightforward mathematical manipulation, and provide a clear interpretation of variability around the most likely value. Consequently, the use of TFNs offers an optimal balance between modeling accuracy and computational simplicity, making this representation suitable for evaluating operational efficiency in air transport under conditions of partial uncertainty [58,59]. Each raw entry x_{ij} (alternative i, criterion j) is fuzzified into a TFN (l_{ij}, m_{ij}, u_{ij}) with a ±5% tolerance, with the membership function $\mu_M(x)$ defined in Equation (1). The resulting fuzzy decision matrix X is given in Equation (2), and its entries (lower/middle/upper components for every criterion) are listed in Table 4.

Step 1 (Fuzzification). Alternatives (observed years) and evaluation criteria are organized in X, where the goal—set by each criterion's positive or negative impact—reflects the assessment of the operational performance of air transport in the Republic of Serbia.

Step 2 (Normalization). Fuzzy entries are normalized according to criterion type using the transformations in Equations (3) and (4) (separate forms for maximizing/beneficial and minimizing/non-beneficial criteria), yielding the normalized fuzzy values r_{ij} = (l_{ij}, m_{ij}, u_{ij}). These normalized TFNs are reported in Table 5.

Step 3 (Aggregation per alternative). The overall fuzzy performance of each alternative $S_i = \left(S_i^L, S_i^M, S_i^U\right)$ is obtained by the logarithmic aggregation given in Equation (5), which mitigates the influence of extremes and preserves the [0, 1] range. The resulting triplets S_i are summarized in Table 6.

Step 4 (Leave-one-criterion-out aggregation). To quantify the "objective importance" of every criterion, we recompute the alternative scores when criterion j is excluded, producing S_{ij} as in Equation (6). This provides a direct counterfactual for each criterion relative to the baseline Si.

Step 5 (Removal effects and defuzzification). For each criterion j, the removal effect E_j is the sum of absolute deviations across all alternatives Equation (7). The fuzzy effects are then defuzzified using the centroid method Equation (8) to obtain crisp impact measures E_j. The fuzzy triplets and their defuzzified values are presented in Table 7.

Step 6 (Final objective weights). The final weights follow by normalizing the defuzzified removal effects Equation (9). For completeness, the fuzzy weight intervals $\left(W_j^L, W_j^M, W_j^U\right)$ and the defuzzified weights w_j are listed in Table 8, verifying $\sum_{j=1}^{m} w_j = 1$.

Table 4. Initial fuzzy decision matrix (TFNs, ±5%; L–M–U components) by alternatives and criteria.

	C_1			C_3			C_5			C_6			C_7			C_9		
	L	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**
A_1	2331.3	2454	2576.7	2230.6	2348	2465.4	1765.1	1858	1950.9	99.75	105	110.25	4427.95	4661	4894.05	151,979.1	159,978	167,976.9
A_2	2509.9	2642	2774.1	2446.25	2575	2703.75	2470.95	2601	2731.05	101.65	107	112.35	4571.4	4812	5052.6	204,864.7	215,647	226,429.4
A_3	2857.6	3008	3158.4	2527	2660	2793	2558.35	2693	2827.65	113.05	119	124.95	4755.7	5006	5256.3	231,224.3	243,394	255,563.7
A_4	3042.85	3203	3363.15	2528.9	2662	2795.1	3004.85	3163	3321.15	114	120	126	5389.35	5673	5956.65	217,342.9	228,782	240,221.1
A_5	2853.8	3004	3154.2	2397.8	2524	2650.2	2957.35	3113	3268.65	106.4	112	117.6	5688.6	5988	6287.4	220,604.3	232,215	243,825.8
A_6	3137.85	3303	3468.15	2642.9	2782	2921.1	3775.3	3974	4172.7	114.95	121	127.05	6251.95	6581	6910.05	274,334.4	288,773	303,211.7
A_7	1153.3	1214	1274.7	847.4	892	936.6	2822.45	2971	3119.55	56.05	59	61.95	1954.15	2057	2159.85	231,664.2	243,857	256,049.9
A_8	1883.85	1983	2082.15	1485.8	1564	1642.2	2682.8	2824	2965.2	76.95	81	85.05	3130.25	3295	3459.75	281,467.9	296,282	311,096.1
A_9	3033.35	3193	3352.65	2584	2720	2856	2863.3	3014	3164.7	114.95	121	127.05	5773.15	6077	6380.85	395,507.8	416,324	437,140.2
A_{10}	4897.25	5155	5412.75	3935.85	4143	4350.15	3581.5	3770	3958.5	174.8	184	193.2	7980	8400	8820	454,405.9	478,322	502,238.1

Table 5. Normalized fuzzy values by criterion.

	C_1			C_3			C_5			C_6			C_7			C_9		
	L	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**
A_1	0.4476	0.4947	0.5468	0.5128	0.5667	0.6264	0.4230	0.4675	0.5168	0.5163	0.5707	0.6307	0.3993	0.4413	0.4878	0.9048	1.0000	1.1053
A_2	0.4157	0.4595	0.5079	0.5623	0.6215	0.6870	0.5922	0.6545	0.7234	0.5261	0.5815	0.6427	0.3868	0.4275	0.4725	0.6712	0.7419	0.8199
A_3	0.3652	0.4036	0.4461	0.5809	0.6420	0.7096	0.6131	0.6777	0.7490	0.5851	0.6467	0.7148	0.3718	0.4109	0.4542	0.5947	0.6573	0.7265
A_4	0.3429	0.3790	0.4189	0.5813	0.6425	0.7102	0.7201	0.7959	0.8797	0.5901	0.6522	0.7208	0.3281	0.3626	0.4008	0.6327	0.6993	0.7729
A_5	0.3656	0.4041	0.4467	0.5512	0.6092	0.6733	0.7087	0.7833	0.8658	0.5507	0.6087	0.6728	0.3108	0.3435	0.3797	0.6233	0.6889	0.7614
A_6	0.3325	0.3675	0.4062	0.6075	0.6715	0.7422	0.9048	1.0000	1.1053	0.5950	0.6576	0.7268	0.2828	0.3126	0.3455	0.5012	0.5540	0.6123
A_7	0.9048	1.0000	1.1053	0.1948	0.2153	0.2380	0.6764	0.7476	0.8263	0.2901	0.3207	0.3544	0.9048	1.0000	1.1053	0.5936	0.6560	0.7251
A_8	0.5539	0.6122	0.6766	0.3416	0.3775	0.4172	0.6429	0.7106	0.7854	0.3983	0.4402	0.4866	0.5648	0.6243	0.6900	0.4885	0.5400	0.5968
A_9	0.3440	0.3802	0.4202	0.5940	0.6565	0.7256	0.6862	0.7584	0.8383	0.5950	0.6576	0.7268	0.3063	0.3385	0.3741	0.3477	0.3843	0.4247
A_{10}	0.2131	0.2355	0.2603	0.9048	1.0000	1.1053	0.8583	0.9487	1.0485	0.9048	1.0000	1.1053	0.2216	0.2449	0.2707	0.3026	0.3345	0.3697

Table 6. Aggregated fuzzy performance S_i of alternatives.

	S_i		
	S_L	S_M	S_U
A_1	0.4476	0.4947	0.5468
A_2	0.4157	0.4595	0.5079
A_3	0.3652	0.4036	0.4461
A_4	0.3429	0.3790	0.4189
A_5	0.3656	0.4041	0.4467
A_6	0.3325	0.3675	0.4062
A_7	0.9048	1.0000	1.1053
A_8	0.5539	0.6122	0.6766
A_9	0.3440	0.3802	0.4202
A_{10}	0.2131	0.2355	0.2603

Table 7. Criterion removal effects.

	E_j		
	E_L	E_M	E_U
C_1	2.27549	1.71349	1.376323
C_3	2.253753	1.563445	1.213827
C_5	2.955355	2.019409	1.544873
C_6	1.963852	1.330587	1.018962
C_7	2.630776	1.989812	1.602705
C_9	1.630087	1.197397	0.947095

Table 8. Final objective weight coefficients.

	W_i			
	W_L	W_M	W_U	**Defuzzy**
C_1	0.165981	0.174594	0.178655	0.173077
C_3	0.164396	0.159305	0.157562	0.160421
C_5	0.215573	0.205765	0.200534	0.207291
C_6	0.143249	0.135579	0.132268	0.137032
C_7	0.191897	0.20275	0.208041	0.200896
C_9	0.118904	0.122007	0.122939	0.121283

Table 9. Obtain weight coefficients.

Criteria	C_1	C_3	C_5	C_6	C_7	C_9
Passenger	0.173077	0.160421	0.207291	0.137032	0.200896	0.121283
Criteria	C_2	C_4	C_5	C_6	C_8	C_9
Freight	0.182659	0.127380	0.184946	0.194570	0.138914	0.171532

For passenger air transport, integrating the initial decision matrix and applying fuzzy MEREC via Equations (1)–(9) yield the weight vector, while the corresponding freight weights are obtained by applying the same procedure to the freight matrix, both presented in Table 9.

The fuzzy MEREC–derived weights indicate distinct importance profiles for passenger and freight air transport. In the passenger case, the distribution is nearly balanced between benefit and cost criteria, with the largest emphasis falling on C_5 and C_7 ($\approx$0.21 and $\approx$0.20), followed by moderate contributions from C_1 and C_3, while C_6 and C_9 are comparatively less influential. By contrast, the freight air transport is more cost-intensive at the criterion level—C_6 is the single most influential factor ($\approx$0.195)—yet, when aggregated by type, the overall structure leans toward benefits because C_2 and C_9 also carry substantial weight. On the common criteria, freight assigns markedly more importance than passenger to C_6 and C_9 (roughly +42% each relative to passenger), whereas passenger assigns more to C_5 (about +11% relative to freight). These patterns imply that, for passenger air transport, performance gains are most effectively achieved by improving outcomes aligned with C_7 while reducing costs associated with C_5, whereas in freight air transport the greatest leverage arises from reducing C_6 (and, secondarily, C_5) alongside strengthening benefit-oriented dimensions such as C_2 and C_9 (Figure 2). Because the two segments are evaluated on partially different sets of criteria, direct cross-segment comparisons are meaningful only for the shared criteria (C_5, C_6, C_9); otherwise, interpretations should remain segment-specific.

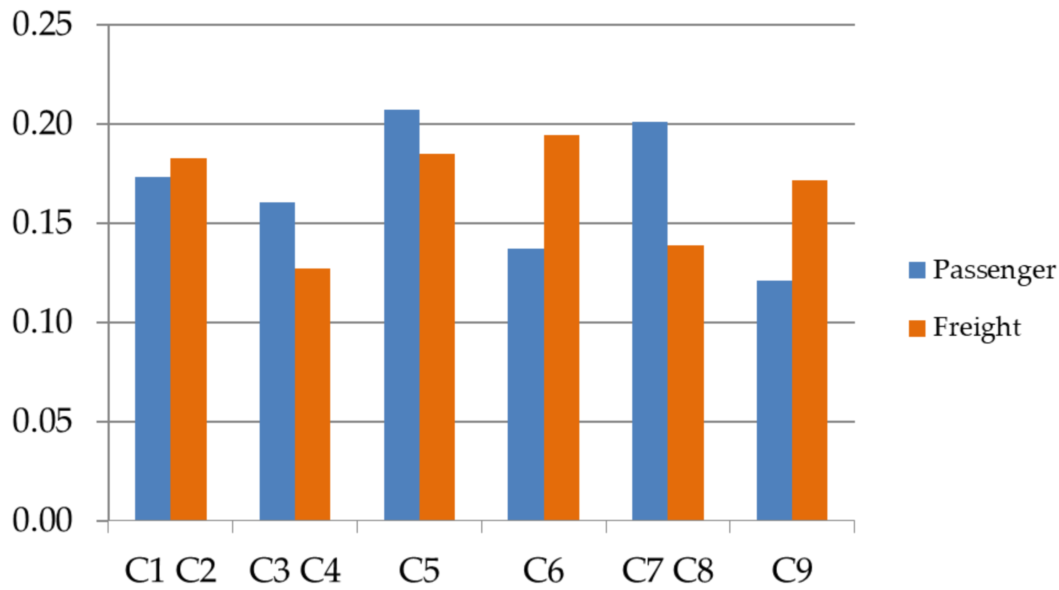

Figure 2. The comparative view of weight coefficients.

4.2. Fuzzy MARCOS Application

When applying the fuzzy MARCOS method Equations (3)–(4) and (10)–(17) to rank operational performance based on selected indicators for passenger and freight air transport during the period from 2014 to 2023, the results show clear temporal patterns of efficiency. Tables 10–12 summarize the normalized decision matrices, weighted normalized values, and final fuzzy scores with corresponding rankings.

Table 10. Normalization of the initial matrix.

	C_1			C_3			C_5			C_6			C_7			C_9		
	L	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**
A_1	0.4522	0.4760	0.4998	0.3618	0.3799	0.3999	0.9524	1.0000	1.0526	0.5351	0.5619	0.5915	0.5271	0.5549	0.5826	0.3177	0.3345	0.3512
A_2	0.4869	0.5125	0.5381	0.3299	0.3464	0.3646	0.6803	0.7143	0.7519	0.5251	0.5514	0.5804	0.5442	0.5729	0.6015	0.4283	0.4508	0.4734
A_3	0.5543	0.5835	0.6127	0.3194	0.3353	0.3530	0.6571	0.6899	0.7262	0.4722	0.4958	0.5219	0.5662	0.5960	0.6258	0.4834	0.5088	0.5343
A_4	0.5903	0.6213	0.6524	0.3191	0.3351	0.3527	0.5594	0.5874	0.6183	0.4683	0.4917	0.5175	0.6416	0.6754	0.7091	0.4544	0.4783	0.5022
A_5	0.5536	0.5827	0.6119	0.3366	0.3534	0.3720	0.5684	0.5969	0.6283	0.5017	0.5268	0.5545	0.6772	0.7129	0.7485	0.4612	0.4855	0.5098
A_6	0.6087	0.6407	0.6728	0.3054	0.3206	0.3375	0.4453	0.4675	0.4921	0.4644	0.4876	0.5133	0.7443	0.7835	0.8226	0.5735	0.6037	0.6339
A_7	0.2237	0.2355	0.2473	0.9524	1.0000	1.0526	0.5956	0.6254	0.6583	0.9524	1.0000	1.0526	0.2326	0.2449	0.2571	0.4843	0.5098	0.5353
A_8	0.3654	0.3847	0.4039	0.5432	0.5703	0.6003	0.6266	0.6579	0.6926	0.6937	0.7284	0.7667	0.3726	0.3923	0.4119	0.5884	0.6194	0.6504
A_9	0.5884	0.6194	0.6504	0.3123	0.3279	0.3452	0.5871	0.6165	0.6489	0.4644	0.4876	0.5133	0.6873	0.7235	0.7596	0.8269	0.8704	0.9139
A_{10}	0.9500	1.0000	1.0500	0.2051	0.2153	0.2266	0.4694	0.4928	0.5188	0.3054	0.3207	0.3375	0.9500	1.0000	1.0500	0.9500	1.0000	1.0500

Table 11. The weighted normalized matrix.

	C_1			C_3			C_5			C_6			C_7			C_9		
	L	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**
A_1	0.0783	0.0824	0.0865	0.0580	0.0609	0.0642	0.1974	0.2073	0.2182	0.0733	0.0770	0.0811	0.1059	0.1115	0.1170	0.0385	0.0406	0.0426
A_2	0.0843	0.0887	0.0931	0.0529	0.0556	0.0585	0.1410	0.1481	0.1559	0.0720	0.0756	0.0795	0.1093	0.1151	0.1208	0.0519	0.0547	0.0574
A_3	0.0959	0.1010	0.1060	0.0512	0.0538	0.0566	0.1362	0.1430	0.1505	0.0647	0.0679	0.0715	0.1137	0.1197	0.1257	0.0586	0.0617	0.0648
A_4	0.1022	0.1075	0.1129	0.0512	0.0538	0.0566	0.1160	0.1218	0.1282	0.0642	0.0674	0.0709	0.1289	0.1357	0.1425	0.0551	0.0580	0.0609
A_5	0.0958	0.1009	0.1059	0.0540	0.0567	0.0597	0.1178	0.1237	0.1302	0.0687	0.0722	0.0760	0.1360	0.1432	0.1504	0.0559	0.0589	0.0618
A_6	0.1054	0.1109	0.1164	0.0490	0.0514	0.0541	0.0923	0.0969	0.1020	0.0636	0.0668	0.0703	0.1495	0.1574	0.1653	0.0696	0.0732	0.0769
A_7	0.0387	0.0408	0.0428	0.1528	0.1604	0.1689	0.1235	0.1296	0.1365	0.1305	0.1370	0.1442	0.0467	0.0492	0.0517	0.0587	0.0618	0.0649
A_8	0.0632	0.0666	0.0699	0.0871	0.0915	0.0963	0.1299	0.1364	0.1436	0.0951	0.0998	0.1051	0.0749	0.0788	0.0827	0.0714	0.0751	0.0789
A_9	0.1018	0.1072	0.1126	0.0501	0.0526	0.0554	0.1217	0.1278	0.1345	0.0636	0.0668	0.0703	0.1381	0.1453	0.1526	0.1003	0.1056	0.1108
A_{10}	0.1644	0.1731	0.1817	0.0329	0.0345	0.0364	0.0973	0.1022	0.1075	0.0418	0.0439	0.0463	0.1909	0.2009	0.2109	0.1152	0.1213	0.1273

Table 12. Final defuzzified scores & ranking.

	S (TFN)			K^+ (TFN)			K^- (TFN)			$S_{Centriod}$	f(k)
	L	**M**	**U**	**L**	**M**	**U**	**L**	**M**	**U**		
A_1	0.551502	0.579663	0.609554	0.8160	0.8576	0.9018	1.0257	1.0781	1.1337	0.58024	1.770069
A_2	0.511456	0.537675	0.565294	0.7567	0.7955	0.8364	0.9512	1.0000	1.0514	0.538142	1.428321
A_3	0.520456	0.547185	0.575241	0.7700	0.8096	0.8511	0.9680	1.0177	1.0699	0.547627	1.500402
A_4	0.517493	0.544121	0.571966	0.7656	0.8050	0.8462	0.9625	1.0120	1.0638	0.544527	1.476857
A_5	0.528375	0.555551	0.583993	0.7817	0.8219	0.8640	0.9827	1.0332	1.0861	0.555973	1.566297
A_6	0.529359	0.55668	0.585081	0.7832	0.8236	0.8656	0.9845	1.0353	1.0882	0.55704	1.575377
A_7	0.550949	0.578876	0.608943	0.8151	0.8565	0.9009	1.0247	1.0766	1.1325	0.579589	1.763076
A_8	0.521568	0.548197	0.57647	0.7717	0.8111	0.8529	0.9700	1.0196	1.0722	0.548745	1.508252
A_9	0.57564	0.605317	0.636233	0.8517	0.8956	0.9413	1.0706	1.1258	1.1833	0.60573	2.011621
A_{10}	0.642531	0.675896	0.710166	0.9506	1.0000	1.0507	1.1950	1.2571	1.3208	0.676197	2.837296

The structured procedure of the MARCOS method begins with the construction of the initial decision matrix, which incorporates n criteria and m alternatives. Once the decision matrix is formed (Step 1), the ideal and anti-ideal solutions are determined for each criterion (Step 2) using the following Equations (10) and (11). The third step involves normalizing the decision matrix according to the type of criterion Equations (3) and (4), as shown in Table 10, followed by the construction of the weighted normalized matrix (Equation (12)), as shown in Table 11.

Utility degrees relative to the ideal and anti-ideal solutions are then computed Equations (13) and (14), while Equations (15) and (16) yield partial utility functions. Finally, Equation (17) derives the overall utility function of each alternative, after which fuzzy results are defuzzified and used for ranking (Table 12). Since fuzzy numbers are applied in the earlier stages, these utility values are subsequently defuzzified to obtain crisp values suitable for ranking. The alternative with the maximum utility value is identified as the compromise solution.

Table 13 shows the annual results for both passenger and freight air transport. The findings indicate that the highest performance was achieved in 2023 for passenger air transport (f = 2.8379), whereas 2014 marked the weakest year for freight air transport (f = 1.1335). The results confirm that passenger air transport efficiency recovered more dynamically after the pandemic shock, while freight air transport demonstrated earlier peaks but greater instability during the 2019–2022 period.

Figure 3 illustrates the annual ranking of operational performance for air passenger and freight transport in the Republic of Serbia from 2014 to 2023. The y-axis represents the ranking positions (with 1 indicating the best performance and 10 the lowest), while the x-axis shows the corresponding years. The blue line with diamond markers denotes the performance ranking of passenger transport, while the orange line with square markers reflects the ranking of freight transport.

Segment by segment, freight exhibits a sustained pre-pandemic climb, improving from 2014 to its apex in 2018 (1st; $f_k = 3.66$), followed by volatility and partial erosion in 2019–2022, and a modest recovery to 4th in 2023. Passenger performance shows early weakness with the nadir in 2015 (10th; $f_k = 1.43$), steady improvement through 2020 (4th; $f_k = 1.76$), a pandemic-related setback in 2021 (7th; $f_k = 1.51$), and then a pronounced rebound to 2nd in 2022 ($f_k = 2.01$) and 1st in 2023 ($f_k = 2.84$).

Table 13. Ranking results for passenger and freight air transport obtained by fuzzy MARCOS method.

	Passenger		Freight	
	f_k	Rank	f_k	Rank
2014	1.770069	3	1.135325	10
2015	1.428321	10	1.217566	9
2016	1.500402	8	1.843869	8
2017	1.476857	9	3.461226	2
2018	1.566297	6	3.658958	1
2019	1.575377	5	2.386161	7
2020	1.763076	4	3.291079	3
2021	1.508252	7	2.943019	5
2022	2.011621	2	2.800847	6
2023	2.837296	1	3.157115	4

Comparatively, freight air transport reached its peak earlier (2017–2018), whereas the passenger air transport segment lagged but delivered the strongest end-of-period acceleration (2022–2023). The crossings and divergent paths of the two series suggest distinct efficiency drivers—such as demand structure, network configuration, and operational constraints—implying differentiated policy levers: consolidate earlier gains in freight air transport while sustaining post-pandemic resilience and service quality in passenger air transport operations.

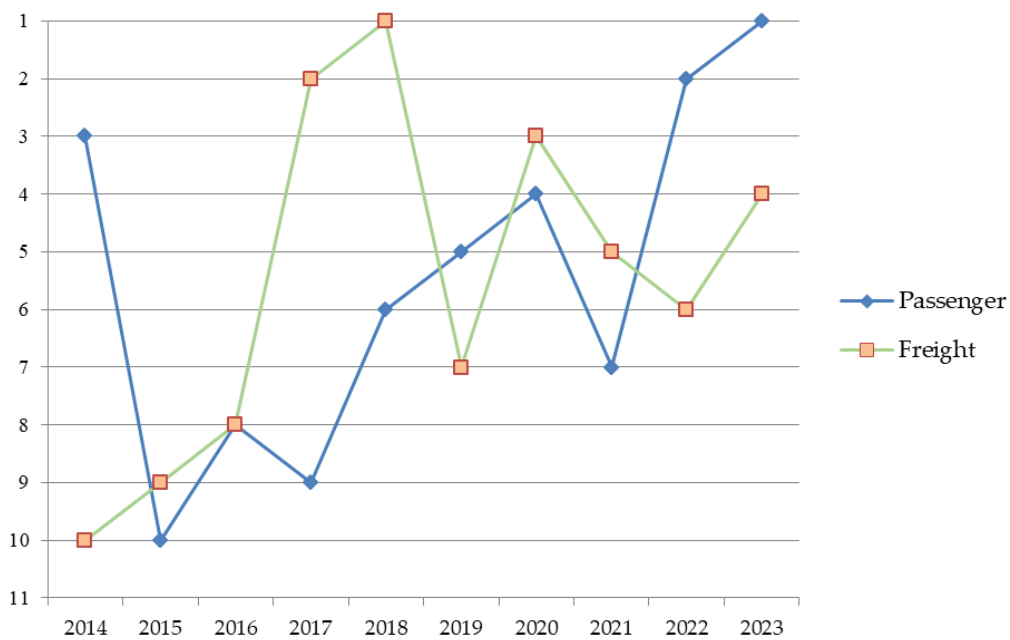

Figure 3. Ranking Diagram of Annual Operational Efficiency of Passenger and Freight Air Transport in Serbia.

The diagram highlights not only the temporal dynamics of air transport efficiency but also the differing sensitivity of the passenger and freight sectors to external disruptions and recovery trends.

As an emerging player in the European air transport landscape, the Republic of Serbia must implement targeted strategies to support further growth. These strategies include the modernization of airport infrastructure, establishment of new air corridors, and upgrades to air traffic control systems, all aimed at improving both the quality and safety of air traffic management. Additional necessary actions involve expanding cargo terminals, enhancing fleet capabilities, and investing in sustainable technologies to improve air transport efficiency and meet the evolving needs of both passengers and freight operators. This would contribute to raising Serbia's air transport quality standards, ensuring it can provide competitive services while addressing the demands of the sector's stakeholders.

5. Sensitivity Analysis

Sensitivity analysis is included to confirm the stability of the weighting coefficients and the robustness of the resulting rankings. This analysis examines how small variations in criterion weights affect the ordering of alternatives, helping determine the degree to which the decision outcome depends on the weighting structure [60–62]. The approach evaluates the smallest change needed to alter relative ranking positions.

The initial ranking for passenger air transport was obtained using six criteria (C_1, C_3, C_5, C_6, C_7, C_9), where C_1, C_7, and C_9 represent benefit-type criteria, and C_3, C_5, and C_6 correspond to cost-type criteria. All indicators were normalized using standard monotone normalization [63], and aggregated through a weighted linear composite model with the weight vector w derived from the fuzzy MEREC procedure [64]. The baseline results are given in Table 14, where alternative A_{10} is identified as the dominant best-performing option.

Table 14. Baseline results (normalized composite score and rank).

Alternative	Score (norm.)	Rank
A_{10}	0.675896	1
A_9	0.605317	2
A_1	0.579663	3
A_7	0.578876	4
A_6	0.556680	5
A_5	0.555551	6
A_8	0.548197	7
A_3	0.547185	8
A_4	0.544121	9
A_2	0.537675	10

To evaluate how ranking positions change under local perturbations, one-at-a-time weight variations were applied following the Absolute-Any (AA), Percent-Any (PA), and Absolute-Top (AT) criteria [65,66]. The thresholds that produce the first rank reversals are presented in Table 15, while the minimal weight shifts that replace the top-ranked alternative are shown in Table 16. The earliest ranking changes occur for the cost criteria C_3 and C_6, where small increases in weight re-order closely ranked alternatives (A_1 and A_7). In contrast, much larger changes in the benefit criteria (C_1 and C_7) are required before the top alternative is affected, indicating strong dominance of A_{10} in the baseline decision setting.

Table 15. AA/PA thresholds (minimal changes that alter the ranking).

Criteria	Δw (abs.)	Δw (%)	First Flip in the Ranking
C_3 (min)	0.001174	0.732	$A_7 > A_1$
C_6 (min)	0.001552	1.132	$A_7 > A_1$
C_7 (max)	0.003985	1.984	$A_3 > A_8$
C_1 (max)	0.004288	2.478	$A_3 > A_8$
C_9 (max)	0.004032	3.325	$A_7 > A_1$
C_5 (min)	0.006945	3.350	$A_5 > A_6$

Table 16. AT thresholds (change of the top alternative).

Criteria	Δw (abs.)	Δw (%)	New Top Alternative
C_1 (max)	0.120291	69.502	A_7
C_7 (max)	0.117894	58.684	A_7

To test robustness within a practically relevant range, a ± 10% variation was applied one criterion at a time, with renormalization to preserve $\sum w_j = 1$ [67]. The resulting Spearman rank correlations remained high ($\rho \geq 0.964$), and no rank reversals of the best-performing alternative were recorded, as shown in Table 17 [68,69]. The same procedure applied to freight air transport produced correlations equal to or very close to unity (Min $\rho \approx 0.988$), confirming complete stability of the ranking within the examined variation interval.

Table 17. Robustness under ±10% one-at-a-time weight changes (Spearman ρ).

Criterion	Min ρ	Mean ρ
C_1	0.963636	0.988485
C_3	0.987879	0.989091
C_5	0.987879	0.990909
C_6	0.987879	0.990303
C_7	0.963636	0.984242
C_9	0.975758	0.992121

These results show that the ranking of alternatives is highly robust, and the selection of the best-performing year remains unchanged under realistic adjustments of criterion weights. Therefore, the integrated fuzzy MEREC–fuzzy MARCOS framework demonstrates strong reliability and suitability for operational performance evaluation in air transport.

6. Conclusions

Based on the results presented and discussed in the previous sections, a final conclusion can be drawn regarding the operational performance of passenger and cargo air transport in the Republic of Serbia. Although this research provides valuable insights into the operational performance of passenger and cargo air transport in Serbia, several limitations should be noted. The analysis is based on available statistical data and does not include qualitative factors such as service quality or customer satisfaction. The selected set of criteria does not incorporate environmental, safety, or service-level indicators, which may also influence performance outcomes. Furthermore, the focus on the Serbian context limits the generalizability of the findings to other regions. Additionally, the results of the fuzzy MCDM methods depend on the chosen methodological assumptions. The evaluation results indicate that freight transport exhibited steady growth until 2018, experienced fluctuations during 2019–2022, and then showed moderate recovery in 2023. In contrast, passenger transport reached its lowest point in 2015, declined again in 2021 following the pandemic, and achieved its strongest recovery and highest performance in 2023. These findings highlight different efficiency drivers and sectoral sensitivities to external disruptions. Despite the outlined limitations, the conducted analysis offers valuable insights into the developmental trends and operational efficiency of air transport in Serbia, thus providing a reliable foundation for informed strategic decision-making and future sector improvement. Moreover, the study contributes to the scientific literature by demonstrating the effectiveness of the integrated fuzzy MEREC–fuzzy MARCOS framework in evaluating air transport performance, offering a methodological reference and practical decision-support tool for resource optimization, efficiency improvement, and long-term policy planning in the air sector.

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