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THE FINANCIAL PERFORMANCE ANALYSIS USING LOPCOW AND AROMAN INTEGRATED MCDM APPROACH: AN APPLICATION IN AIRPORT GROUPS

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Abstract:
Airport groups are companies that deliberately expand their portfolio of domestic or international airports, resulting in a large number of airports under their management. These groups are among the aviation sector's most important stakeholders. Despite the growing importance of airport groups, they have been largely neglected in the literature. The study aims to analyze the performance of airport groups by evaluating financial performance in a multidimensional manner through the inclusion of per-share metrics alongside traditional financial indicators. In this context, the study examined 11 airport groups in five dimensions. The study used the integrated MCDM approach developed by LOPCOW and AROMAN. The findings revealed that the financial structures and profitability of Airport Groups were decisive in performance in the pre-pandemic (2018-2019), pandemic (2020-2021) and post-pandemic (2022-2023) periods. Furthermore, the geographical diversity of the airports operated and the impact of the pandemic on the financial performance of airport groups were effective.

Key words: *Airport groups, Financial performance, Lopcow Method, Aroman Method.*

1. Introduction

Airport groups are an important stakeholder group within the air transport system. Following the privatisation of airlines in the United States in 1978, many other regions initiated a process of partial or full privatisation of airlines. This has led to increased competition among airlines. Increased competition, lower ticket prices and an increased number of flights have changed the structure of airports. Airports, which were previously considered “public services”, have gradually transformed into state-owned, profit-making enterprises. This has effectively transformed airports into commercial enterprises.

The privatisation of airports began in Europe in the late 1980s. Following the privatisation of the British Airports Authority (BAA), a number of airport groups emerged, including Aéroports de Paris, Schiphol Group and Fraport Airport Group. Today, these groups primarily focus on airport operations. As a result, airport groups have deep know-how in the efficient operation of airports. Airport groups also engage in various airport-related activities, including planning, engineering, and construction (ACI, 2019). By 2022, these groups had generated total revenues of USD 38.9 billion, accounting for one-third of the global airport revenue (CAPA, 2024). Therefore, evaluating the efficiency and financial health of these groups provides valuable insights for policymakers, investors, and stakeholders in the aviation industry.

According to Nerja & Sánchez (2021), the liberalisation of the airline market and subsequent privatisation of airports has intensified competition among airport groups. This has prompted airport operators to adopt new strategies in order to gain a competitive advantage. Currently, certain airport groups operate many airports in different geographies around the world and operate on a global scale. Furthermore, 27 airport groups operate at 425 airports. These groups manage 29% of global passenger traffic and 23% of cargo tonnage. Additionally, the five largest airport groups had a combined revenue of USD 38.9 billion in 2022. This accounts for 32.5% of the USD 119.8 billion world airport revenue in 2022 (CAPA, 2024). Airport groups are therefore competing to increase their total revenues and operate new airports in larger regions. This highlights the importance of financial indicators such as profitability, cost and return on assets.

Over the past decade, studies on airports, particularly those focusing on airport competition, have attracted considerable interest from researchers. Lian and Rønnevik (2011), for example, focus on competition between regional and large airports. The findings of the study show that airports may experience increased losses as competition increases due to the large differences in traffic and fares from regional airports to major airports. Pels et al. (2009) examined the impact of low-cost airlines on airport competition. In the study, cross-price elasticities of demand structure were estimated using logit model. The results showed that especially cross-price elasticities were lower than expected. Bao et al. (2016) analysed the impact of airport accessibility on airport competition. In this study, panel data analysis was employed and airport accessibility was identified as an important factor affecting the transportation speed, cost and comfort of passengers. Starkie (2002) analysed the impact of regulations on airport competition. The results suggest that, although there are substitution possibilities among airports depending on certain circumstances, regulation based on normal competition laws can sufficiently limit monopolistic behaviour. Pagliari & Graham (2019) focus on the impact of ownership changes on airport competition. Their findings suggest that, following a change in ownership, there was an increase in traffic and the number of routes at airports, as well as an increase in fees and greater price differentiation. There were also improvements in efficiency and service quality in some performance indicators. Thelle & Sonne (2018) empirically examine competition among European airports. The results demonstrate that, with airlines and passengers having more choice, airports now face stronger competitive pressures and must be implemented selectively based on market power. The existence of studies on airport competition provides important evidence of the significance of profitability in the airport industry.

Airport profitability has been widely studied in the literature. Studies have examined various factors influencing airport profitability (Fuerst & Gross, 2018; Zuidberg, 2017), the relationship between service quality and airport profitability (Merkert & Assaf, 2015), airport commercial performance (Raghavan & Yu, 2021; Vasigh & Hamzaee, 1998), the impact of ownership structure on airport profitability (H. A. Vogel, 2011; H.-A. Vogel, 2006), and optimal pricing strategies to maximise airport profitability (Zhang & Zhang, 1997). Studies on airport groups typically focus on classifying airports based on various characteristics such as flight traffic, hub status, and passenger volume. Therefore, unlike the subject of this study, these works result from clustering airports according to certain features and referring to these clusters as "airport groups" (Adler & Liebert, 2014; Kalakou & Macário, 2013; lo Storto, 2018; H. A. Vogel & Graham, 2013; Yu, 2023). In contrast to these studies, this research focuses on the evaluation of the financial performance of airport operating companies (referred to as airport groups), including the period affected by the Covid-19 pandemic.

There is a very limited number of studies on "airport groups" operating airports across different regions. Among these, Forsyth et al. (2011) examined how collaborations and mergers in airports shape the cross-ownership structures of airports and their impact on key drivers. The results of the study suggest that although the recent wave of privatization in the airport sector has brought about some mergers, the idea that this process will produce similar results to alliances in the airline sector is misleading. Bel (2009) examined the competitive impact of the Aeropuertos Españoles y Navegación Aérea (AENA) airport group on air transportation services in Girona. The findings of the study reveal that the demands of low-cost airlines are based on the infrastructure and regional characteristics suitable for them, as well as the commercial and financial incentives of local governments to increase airline traffic. Ferreira et al. (2016) examined the performance of airports analyzed by airport groups and individual airports. The results reveal that European airports are the most productive. Martínez et al., (2023) examined the privatization of the AENA airport group as a case study. The findings of the study indicate that the Aena case study was an educational tool for students to develop their financial analysis and valuation skills in a holistic manner. Graham (2020) evaluated the privatization of airports for individual and group airports, taking into account the regulatory and competitive operating environment. The study highlights the need for greater focus on governance and institutional structures due to the diversity of privatization models. Özcan (2019) conducted one of the few studies on airport groups. This study analysed the impact of the capital structure of public airport groups on their profitability and market capitalisation. The data of 29 publicly traded airport groups were analysed using unbalanced panel data analysis. The findings revealed that higher levels of total and long-term debt tend to reduce return on assets. However, to our knowledge, no study has examined the financial performance of airport groups. Furthermore, assessing the impact of the pandemic on the financial performance of airports is crucial for investors and decision-makers alike. Therefore, this study is expected to contribute to the literature in two ways: Firstly, it draws attention to airport groups that are more neglected in the literature by examining them. Secondly, it will contribute to the literature by revealing the current situation through analysis of the performance of airport groups before and after the pandemic.

In this study, the integrated LOPCOW and AROMAN methods were employed. The reasons for using the LOPCOW method in this study are as follows; (I) it is an objective weighting method with a simple mathematical structure, (II) it has a very short calculation time and strong calculation capability, (III) no software program is required during use, (IV) negative values in the dataset can be included directly in the analysis without transformation and (V) it has an algorithm that eliminates differences due to data size (Ecer & Pamucar, 2022). The AROMAN method was chosen because (I) it differentiates between benefit- and cost-oriented criteria in the dataset, (II) it offers a practical, simple ranking approach that avoids complex calculations, (III) it allows for both quantitative and qualitative evaluation of decision alternatives and (IV) it produces more robust ranking results by applying two types of normalisation process (Bošković et al., 2023a).

The continuation of this study is planned as follows: The second section will present studies from the literature. The third section will cover the data and methods used in the study. The fourth section will discuss the findings obtained from the study in relation to similar studies in the literature. The results of the study will be presented in the fifth section.

2. Literature

Financial performance is an important component of airport management and is often assessed using metrics such as profitability, cost effectiveness and revenue generation. This section reviews research on airport performance. This research can be categorised into two main groups. The first category is individual airports, and the second is airport groups. Some of these studies are presented in this section.

Fung et al. (2008) employed Malmquist total factor productivity analysis to demonstrate the evolution of productivity levels at 25 regional airports in China. They found that the average annual growth in airport productivity was over 3%, with technical progress emerging as the main driver of this growth rather than efficiency improvements. Roghanian & Foroughi (2010) conducted an empirical study of Iranian airports, evaluating the productivity of different airports using Data Envelopment Analysis (DEA) methodologies. A major challenge with many traditional DEA approaches is that the data is often affected by noise. This study utilises a DEA approach that can manage the uncertainty associated with input and output data. This comprehensive analysis revealed that many existing airports were inefficient, and that the government could significantly improve efficiency by implementing new regulations and policies. Yeh et al. (2011) present a fuzzy multi-criteria decision-making approach for evaluating airport performance, focusing on dimensions relating to operators, passengers, and airlines. The algorithm uses the α-cut concept to incorporate the decision maker's level of confidence into the participants' fuzzy evaluations. This generates a quantitative performance index for each airport, providing insight into their operational management, facilities, and passenger service quality performance. Vogel & Graham (2013) employed cluster analysis to identify groups of airports for comparative financial and economic performance studies. They used 73 airports from around the world and nine key performance indicators to identify clusters. Three clusters were formed: one dominated by North American airports; one dominated by European airports; and one dominated by non-North American airports.

Asker & Kiracı (2016) analysed the financial statements of five large airport groups established and operating in Europe between 2007 and 2014, using the trend analysis method. The study revealed that some airports followed an upward trend while others followed a downward trend, using various financial indicators. Liu (2016) evaluated the efficiency of the aviation and commercial service sub-processes of ten East Asian airport groups between 2009 and 2013. He used Network Data Envelopment Analysis (NDEA) and a panel data model to identify the key influencing factors. The initial NDEA results revealed that only the Hong Kong Airport Authority performed efficiently in both sub-processes, achieving overall efficiency. Beijing Capital International Airport Co., Ltd. and Shanghai International Airport Co., Ltd. performed efficiently in the aviation service sub-process, while Hong Kong Airport performed efficiently in the commercial service sub-process. Keskin & Ulaş (2017) examined the impact of privatisation and deregulation strategies on the performance of the twenty busiest airports in Europe, using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and DEA. The evaluation criteria included passenger numbers, operational revenue, the number of runways, cargo traffic, and aircraft movements. The study compares the performance of private and publicly owned airports.

Lee and Park (2018) emphasised the importance of creative communication, convergence, and identity in airport operations. This research confirms that diversity influences airport performance and that the mediating effect of creativity and the moderating effect of public enterprise management play a role in airport operations. In the context of Incheon and Gimpo international airports in Korea, the findings show that positive internal diversity, mediated creativity and moderate public enterprise management evaluation affect airport performance. Shojaei et al. (2018) proposed a model for evaluation and ranking that integrates the Taguchi Loss Function, the Best-Worst Method (BWM), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique. The researchers enable decision-makers to set different target values and consumer tolerance thresholds for each criterion, depending on which airports are being ranked, and reduce the number of pairwise comparisons using BWM. A case study of 21 Iranian airports revealed the best performers. Lu et al. (2018) applied the model to three international airports in Taiwan, integrating qualitative and quantitative information using MCDM models, and found that airport image was the most important factor and that the social perspective had the highest net impact. According to the researchers, public transport and financial transparency are the areas with the largest weighting gaps, which have implications for management. Eshtaiwi et al. (2018) aimed to provide Libyan airport sector decision makers with a practical framework for measuring and monitoring performance over time using key performance indicators (KPIs). They used the Analytical Hierarchy Process (AHP) technique to derive weights and select the best international airport based on expert opinions. The study presents the relative importance of seventeen KPIs relating to five aspects of airport performance. This allows Libyan airports to benchmark their performance against others, either externally or internally.

Kumar et al. (2020) employed a combination of the Best-Worst Method (BWM) and VIKOR methodologies to calculate the weights of various criteria and rank airports accordingly in their study aimed at evaluating the green performance of airports. The findings indicate that green policies and regulations are the most significant performance criteria for green airports. Battal (2020) analysed the financial performance of airport groups in Europe using Data Envelopment Analysis (DEA). In this context, six airports were evaluated, and it was revealed that three of them were operating efficiently. Chakraborty et al. (2020) examined the application of BWM and the Multi-Attributive Border Approximation Area Comparison (MABAC) method to assess the performance of 32 major international airports in India based on eight evaluation criteria. Annual revenue was identified as the most critical evaluation criterion, followed by the total number of passengers. Based on this comprehensive analysis, Indira Gandhi International Airport was found to be the best-performing international airport in India, while Surat International Airport was considered the least effective.

Merdivenci et al. (2021) aimed to develop sustainable performance software for airports by analysing economic, social, and environmental parameters. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Ordinal Measurement Approach (OMAX) methods were employed to evaluate performance indicators in the context of Antalya Airport. The findings indicated that the most critical criterion for Antalya Airport was the economic aspect. Sustainable performance scores were calculated for the years 2018 and 2019, revealing that performance in 2019 was higher compared to 2018. Ersoy (2021) assessed the performance and ranking of major international airports during the first quarters of 2019 and 2020 using Data Envelopment Analysis (DEA), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Evaluation Based on Distance from Average Solution (EDAS) methods. While efficiency analysis was conducted using the CCR-DEA model, performance evaluations were performed through the TOPSIS and EDAS methods. The study demonstrated that the combined use of DEA and multi-criteria decision-making (MCDM) methods provides a clear ranking of decision-making units (DMUs). Similarly, Durmuşçelebi & Kiracı (2022) evaluated the performance of major airports in Turkey for the period 2013–2019 using the CRITIC-based EDAS method, and observed notable improvements in the performance of several airports over the years.

Işıldak et al. (2023) employed the Integrated Determination of Criteria Weights (IDOCRIW) and Weighted Euclidean Distance Based Approach (WEDBA) methods to evaluate the performance of Tekirdağ Çorlu Airport in Turkey, identifying the best-performing years between 2017 and 2021. The study found that 2021 was the year with the lowest performance, while 2018 was identified as the best-performing year. Gültekin & Çarıkçı (2023) analysed the financial performance of Turkey-based TAV Airports Holding and Germany-based Fraport AG between 2018 and 2021. The Entropy and TOPSIS methods were used to determine the weights of the evaluation criteria. TAV Airports was found to be more successful in 2018, 2019, and 2020, whereas Fraport AG ranked second in 2021 due to a decline in cash and cash equivalents, a reduction in current assets, and fluctuations in exchange rates. Using benchmarking analysis, Giovanelli et al. (2023) explored the impact of ownership structure and airport size on financial performance. Their analysis of 188 airport groups managing 393 European commercial airports revealed that relatively larger companies exhibited higher indebtedness ratios, while smaller companies demonstrated stronger liquidity performance but lower profitability. Additionally, private airports were found to outperform their public counterparts.

The number of studies focusing specifically on airport groups in the literature is quite limited. Moreover, multi-criteria decision-making (MCDM) methods such as DEA, CRITIC, EDAS, AHP, TOPSIS, and VIKOR are frequently utilized to assess financial performance or operational efficiency. These studies often investigate financial performance in relation to ownership structure (e.g., public vs. private), operating models, or regional distinctions. Furthermore, research conducted across various geographical and economic contexts enables international comparisons.

In the present study, airport groups—which are underrepresented in the existing literature—are included in the analysis. Unlike previous studies that typically focused on groups operating within a specific region (e.g., the European Union or Asia-Pacific), this research offers a global framework by incorporating airport groups from across different regions of the world. Additionally, financial performance is evaluated over a broader time span and through the application of novel MCDM methods such as LOPCOW based AROMAN.

3. Data and methodology

This study analyses the financial performance of airport groups over the period 2018–2023. A total of 11 airport groups were examined using 20 criteria across five dimensions to provide a comprehensive assessment of their financial performance. By incorporating multiple dimensions, the study aims to capture the multidimensional nature of financial performance. The LOPCOW method was employed to determine the weights of the criteria, while the AROMAN method was used to rank the financial performance of the airport groups.

The study uses a sample of leading airport groups that operate globally and manage major air transport networks on different continents. These organizations represent a variety of management models, operating in both public and private structures. The selected entities operate major urban airports in regions such as Europe, Asia, Southeast Asia and Latin America, and have a decisive position in the sector in terms of annual passenger volumes, revenue levels and international business partnerships. Moreover, some of these groups hold operating rights not only in their home countries but also in airports abroad. This diversity allows for a comparison of different structural and managerial characteristics in the global airport operations. With their high passenger traffic, multi-airport management, international investment activities and publicly traded financial structures, these organizations provide a suitable sample to assess the financial performance of the sector. In particular, they vary in terms of annual revenue levels, investment strategies, indebtedness ratios and profitability indicators, allowing for a comparative analysis of different financial structures in global airport operations.

The study also used sensitivity analysis and various multi-criteria decision-making (MCDM) methods for validation purposes. The analysis period will shed light on the financial performance of airport groups before and after the onset of the pandemic. The determination of the criteria is based on Wang studies (Wang, 2008, 2014) after an extensive literature review, but the criteria in these studies are not limited to the criteria in these studies and per share values criteria are added to them. The criteria used in the study and their dimensions are shown in Table 1.

Table 1. Performance indicators used in the analysis

Attribute	Code	Formula
Financial structure ratios	C1	Fixed assets/total stockholder's equity
	C2	Fixed assets/long-term liabilities
	C3	Total liabilities/total assets
	C4	Total stockholder's equity/total liabilities
Liquidity ratios	C5	Current assets/current liabilities
	C6	Cash and cash equivalent/current assets
	C7	Net cash from operating activities/current liabilities
	C8	Working capital/current assets
Operational efficiency ratios	C9	Operation cost/accounts payable
	C10	Operation cost/accounts receivable
	C11	Operation revenue/fixed assets
	C12	Operation revenue/total assets
Profitability ratios	C13	Income before tax/operation revenue
	C14	Net income (loss)/operation revenue
	C15	Net income (loss)/total assets
	C16	Net income/total capital
Per share values	C17	Book value per share
	C18	Cash flow per share
	C19	Earnings per share
	C20	Sales per share

Various financial ratios can be derived from the balance sheet and income statement. Some of these financial ratios share similar formulations and patterns, which can lead to redundancy in the analysis phase. To avoid repetitive evaluations, it is important to group (cluster) these ratios into distinct financial clusters and select a representative indicator as an evaluation criterion for each cluster (Pedrycz & Vukovich, 2002; Wang, 2008). The criteria used in this study were determined as a result of analyzing many studies in literature. In this context, Wang studies were taken as basis in determining the criteria (Wang, 2008, 2014). However, by adding a new dimension—per share values—to the evaluation criteria, this study aims to provide a broader analytical perspective for measuring the financial performance of airport groups. Focusing on per share indicators is intended to yield more precise and detailed insights into the financial performance of these groups.

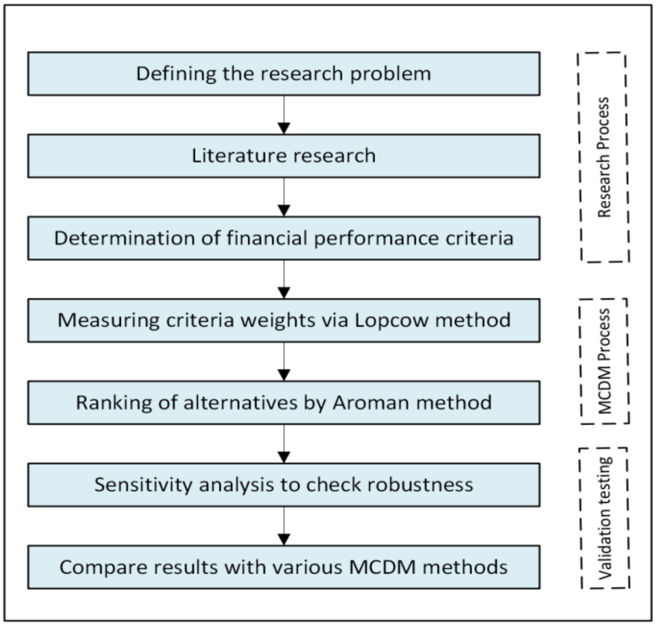

Figure 1. Flow chart of the application model

Figure 1 illustrates the research design of the study. Following the identification of the research problem, financial performance criteria were determined based on a review of the existing literature. The LOPCOW method was employed to assign weights to the criteria, while the AROMAN method was used to rank the airport groups. To ensure the validity of the results, a sensitivity analysis was conducted, along with comparisons using other MCDM methods from the literature.

3.1. LOPCOW Method

The LOPCOW (**LO**garithmic **P**ercentage **C**hange-driven **O**bjective **W**eighting) technique is a novel weighting method proposed by Ecer and Pamucar (2022). It is designed to prioritize evaluation factors within a hierarchical structure in decision-making processes. LOPCOW offers several important advantages. For instance, it effectively addresses issues related to negative or zero values in raw data and provides a rational approach for determining the importance of criteria. Additionally, it produces logical weightings, minimizes the influence of specific characteristics of the criteria that may be impractical or costly, and helps eliminate dimensional inconsistencies caused by data structure (Ulutaş et al., 2024). The LOPCOW method comprises the following steps (Ecer & Pamucar, 2022):

Step 1. Constructing an initial decision matrix (IDM) (Equation 1) for a decision-making problem with *m* number of alternatives and *n* number of criteria.

$$IDM = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2. In this step, the IDM is normalized. The linear max-min normalization technique is used to obtain the normalized values of the elements of the IDM. If *j* is the cost criterion, we go to equation (2) and if *j* is the benefit criterion, we go to equation (3).

$$r_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \qquad if\ j \in C \tag{2}$$

$$r_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \qquad if\ j \in B \tag{3}$$

Step 3. The percentage values (PV) of each criterion are calculated using equation (4). In this step, the mean square value as a percentage of the standard deviations of each criterion is calculated to eliminate the difference (gap) due to the size of the data.

$$PV_{ij} = \left| \ln \left\{ \frac{\sqrt{\frac{\sum_{j=1}^{m} r_{ij}^{2}}{m}}}{\sigma} \right\} * 100 \right| \tag{4}$$

Here σ and m represent the standard deviation and the number of alternatives, respectively.

Step 4. Each criterion weight is calculated through equation (5).

$$W_j = \frac{PV_{ij}}{\sum_{j=1}^{n} PV_{ij}} \tag{5}$$

Equation (5) satisfies the condition that the sum of the weights is $\sum_{j=1}^{n} w_j = 1$

3.2. AROMAN method

AROMAN (**A**lternative **R**anking **O**rder **M**ethod **A**ccounting for Two-Step **N**ormalization) is a ranking technique first introduced by Bošković et al. (2023a) for electric vehicle selection. This innovative method was developed to address the need for effective decision-making in multi-criteria environments. AROMAN employs a two-stage normalization process to enable fair and unbiased comparisons among alternatives. The method supports the construction of a comprehensive ranking order by considering both the relative importance of the criteria and their assigned weights (Bošković et al., 2023b). The AROMAN method consists of the following steps (Bošković et al., 2023a):

Step 1. The initial decision-making matrix (IDM) needs to be defined with input data. Before the decision-making procedure begins, the IDM matrix with input data needs to be defined. Depending on the problem, the input data regarding alternatives and criteria are mostly collected in advance. The initial decision matrix $X = [xij]_{m\times n}$ is defined with *m* number of alternatives and *n* number of criteria.

Step 2. Once the decision-making matrix has been defined and the input data entered, the next step is to normalise the data. This involves structuring the data in ranges between 0 and 1. There are two types of normalization, equation (6) and (7).

$$T_{ij} = \frac{X_{ij} - X_{min}}{X_{max} - X_{min}}, \qquad j = 1,2, \dots, n;\ i = 1,2, \dots, m. \tag{6}$$

$$T_{ij}^{*} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^{2}}}, \qquad j = 1,2, \dots, n;\ i = 1,2, \dots, m. \tag{7}$$

The normalization techniques in Step 2 are used for both types of criteria (min and max).

Step 3. Aggregated mean normalization is performed by applying Equation 8 below.

$$T_{ij}^{norm} = \frac{\beta * T_{ij} + (1-\beta) * T_{ij}^{*}}{2}, \qquad j = 1,2,\dots,n;\ i = 1,2,\dots,m. \quad (8)$$

Where T_{ij}^{norm} refers to the aggregated mean normalization. β is the weight of the linear normalization method, ranging from 0 to 1.

Step 4. To obtain a weighted decision-making matrix, the criteria weights are multiplied by the Summed Mean Normalized decision-making matrix via Equation (9).

$$T^{\wedge}{}_{ij} = W_{ij}\ X\ T_{ij}^{norm}, \qquad j = 1,2,\dots,n;\ i = 1,2,\dots,m. \quad (9)$$

Step 5. The normalized weighted values of criteria of type min (L_i) and the normalized weighted values of type max (A_i) are calculated separately.

$$A_i = \sum_{j=1}^{n} T^{\wedge}{}_{ij}^{max}, \qquad j = 1,2,\dots,n;\ i = 1,2,\dots,m. \quad (10)$$

$$L_i = \sum_{j=1}^{n} T^{\wedge}{}_{ij}^{min}, \qquad j = 1,2,\dots,n;\ i = 1,2,\dots,m. \quad (11)$$

Step 6. The final ranking of the alternatives is calculated. To obtain the final ranking of the alternatives (R_i), Equations (12), (13) and (14) need to be applied. The alternative with the highest value of (R_i), is considered as the best alternative.

$$A^{\wedge}{}_i = A^{1-\tau}{}_i = \{\sum_{j=1}^{n} T^{\wedge}{}_{ij}^{max}\}^{1-\tau}, \quad j = 1,2,\dots,n;\ i = 1,2,\dots,m. \quad (12)$$

$$L^{\wedge}{}_i = L^{\tau}{}_i = \{\sum_{j=1}^{n} T^{\wedge}{}_{ij}^{min}\}^{\tau}, \quad j = 1,2,\dots,n;\ i = 1,2,\dots,m. \quad (13)$$

$$R_i = e^{(A^{\wedge}{}_i - L^{\wedge}{}_i)}, \quad i = 1,2,\dots,m. \quad (14)$$

The λ value in the formula expresses the coefficient degree of the criterion type. In order to calculate the degree of benefit of the alternatives, the value of λ should be $0 < \lambda < 1$.

4. Results

In this part of the study, the LOPCOW and AROMAN methods are employed to evaluate the financial performance of airport groups over the period 2018–2023, focusing on 20 criteria. Then, a sensitivity analysis is performed to examine the effect of changes in weighting on the ranking results. Finally, to increase the reliability and robustness of the proposed model's results, the obtained ranking results are compared with those from other MCDM methods.

4.1. LOPCOW results

In this section, the weights of the financial ratios in the initial decision matrix (IDM) of the airport groups are determined by the LOPCOW method. In the first step of the analysis, an IDM was constructed consisting of alternatives (airport groups) and criteria (financial ratios) as expressed in Equation 1. In the second step of the analysis, the criteria are normalized according to whether they are benefit or cost oriented by means of Equation 2-3. In the third step of the analysis, the percentage value (PV_{ij}) of each criterion was calculated using Equation 4. In the last step of the analysis, the weight values of the criteria

(W_j) were calculated. The LOPCOW application of the research was carried out separately for each year for the period 2018-2023. However, in order to save space, the analysis is presented in detail exclusively for the 2023 data in Annexes (Table 1-4).

The weight values (W_j) of the criteria (financial ratios) for the period 2018-2023 are given in Table 2. When the table is analysed, it can be seen that the criteria change both within themselves and over time. It is seen that the criteria with the highest weight on the financial performance of the airport groups are Net Income / Operating Revenue in 2018 and 2021, Fixed Assets / Total Stockholder's Equity in 2019, 2022 and 2023 and Net Income / Total Capital in 2020. The criteria with the lowest weights are Operation Revenue / Fixed Assets in 2018-2019, Fixed Assets / Long-Term Liabilities in 2020, Book Value Per Share in 2021 and 2023, and Before Tax / Operation Revenue in 2022.

Table 2. LOPCOW method performance criteria weight

	2018	2019	2020	2021	2022	2023
C1	0,037621	**0,101574**	0,096415	0,088576	**0,118833**	**0,116094**
C2	0,022297	0,013738	0,010082	0,022579	0,031093	0,038147
C3	0,072128	0,067397	0,051155	0,062107	0,079625	0,080430
C4	0,030725	0,025229	0,012538	0,040084	0,055535	0,051836
C5	0,043102	0,037762	0,032971	0,018978	0,062778	0,033350
C6	0,051234	0,040852	0,039746	0,050776	0,065657	0,060584
C7	0,040665	0,038713	0,037222	0,064265	0,050410	0,045273
C8	0,091894	0,090246	0,066412	0,039411	0,100338	0,057823
C9	0,040952	0,077266	0,061456	0,080211	0,076611	0,094011
C10	0,090214	0,069055	0,082160	0,063450	0,085360	0,070806
C11	0,020554	0,012263	0,069557	0,045121	0,008286	0,022955
C12	0,047749	0,033389	0,043624	0,045916	0,052709	0,020764
C13	0,043731	0,084465	0,020627	0,073931	0,001913	0,035348
C14	**0,102426**	0,081936	0,044454	**0,090699**	0,005920	0,108889
C15	0,073663	0,072628	0,072207	0,047991	0,062061	0,038554
C16	0,084838	0,081111	**0,098605**	0,038618	0,064558	0,046256
C17	0,024188	0,017707	0,016440	0,014837	0,017664	0,017620
C18	0,023984	0,018111	0,033477	0,016186	0,019237	0,019537
C19	0,031859	0,017742	0,089241	0,077477	0,017876	0,018719
C20	0,026175	0,018817	0,021610	0,018786	0,023533	0,023005

4.2. AROMAN results

In this section, the performance ranking of airport groups operating in various regions of the world is analysed using the AROMAN method. As stated in Equation 1, an IDM consisting of alternatives (airport groups) and criteria (financial ratios) was constructed. The criteria were then subjected to linear and vector normalization by means of Equation 6 and Equation 7. In the next step, the two differently normalized matrix were combined using Equation 8. In the aggregation process, the indicator (β) was taken as 0.5. Then, the weight values obtained by the LOPCOW method are included in the analysis through Equation 9. In the next step, (A_i) and (L_i) values of the alternatives were calculated using Equation 10-11. In the last step of the analysis, the final ranking of the alternatives was obtained by calculating their (R_i) values using Equation 12-14. The Aroman application of the research was conducted separately for each year for the period 2018-2023. However, in order to save space, only the analyses for 2023 are presented in detail in Annexes (Table 5-9).

According to the AROMAN method, the ranking results of the alternatives (airport groups) for the period 2018-2023 are shown in Figure 2.

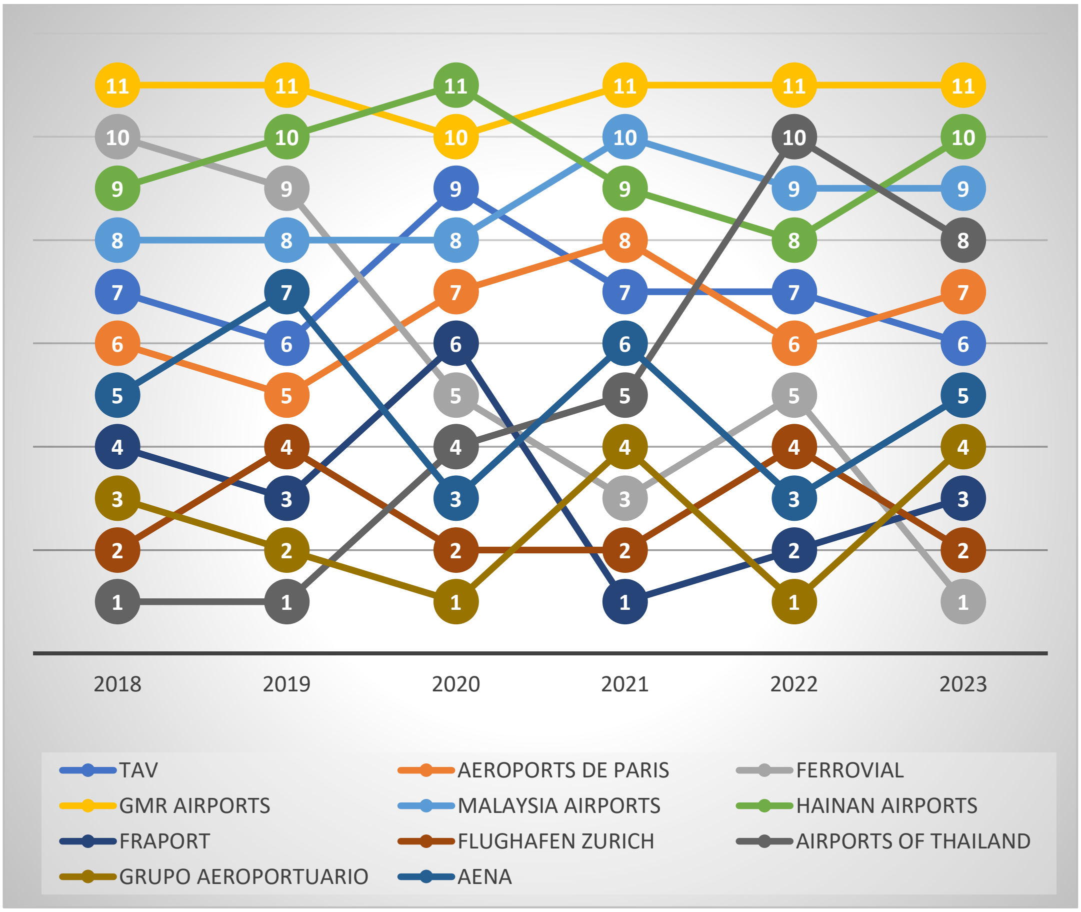

Figure 2. Performance ranking of airport groups according to the AROMAN method (2018-2023)

Figure 2 presents the financial performance rankings obtained using the AROMAN method. According to the results, Airports of Thailand demonstrated the highest financial performance in 2018 and 2019, Grupo Aeroportuario ranked first in 2020 and 2022, Fraport led in 2021, and Ferrovial achieved the top position in 2023. On the other hand, GMR Airports exhibited the weakest performance in 2018, 2019, and from 2021 to 2023, while Hainan Airports recorded the lowest performance in 2020.

The results also indicate a notable decline in the financial performance of TAV, Aéroports de Paris, Fraport, and Airports of Thailand in 2020 compared to 2019. This decrease is primarily attributed to a deterioration in their liquidity structures due to significant revenue losses during the pandemic. Conversely, Ferrovial, Flughafen Zürich, Grupo Aeroportuario, and AENA experienced improved performance in 2020, likely owing to their strong liquidity positions that allowed them to weather the financial challenges more effectively.

In 2021, Ferrovial, Fraport, Hainan Airports, and TAV showed improved performance compared to the previous year. This recovery is thought to be driven by the easing of travel restrictions and the support of government subsidies. In contrast, Aéroports de Paris, Malaysia Airports, Airports of Thailand, Grupo Aeroportuario, and AENA underperformed relative to 2020, suggesting that despite the partial recovery from the COVID-19 crisis, these airport groups struggled to generate sufficient cash flow and strengthen their financial structures.

In 2022, the financial performance of AENA, Aéroports de Paris, Grupo Aeroportuario, Hainan Airports, and Malaysia Airports improved compared to 2021. This indicates that these airport groups demonstrated a faster recovery in the post-pandemic period relative to their counterparts.

4.3. Robustness and Validation

At this stage of the analysis, a two-step sensitivity analysis was conducted to assess the applicability and robustness of the proposed model. The first step tested the robustness of the objective weighting method (LOPCOW), while the second step examined the robustness of the ranking method (AROMAN). Specifically, the analysis first investigated whether changes in the criteria weights would affect the ranking results. To this end, 20 different scenarios were developed based on the criterion with the highest weight (C1), as determined by the LOPCOW method for 2023. The weights for these scenarios were calculated using Equation (15).

$$W_{n\beta} = (1 - W_{n\alpha}) * \frac{W_\beta}{(1 - W_n)} \tag{15}$$

$W_{n\beta}$ is the weights for the scenario, $W_{n\alpha}$ is the reduced values of the variable with the highest weight (C1), W_β is the original weights of the criteria and W_n is the original weight of the variable with the highest weight (C1) (Kirkwood, 1997). In this study, $W_{n\alpha}$ is applied as 5% due to 20 scenarios. The weight values for the criteria are shown in Figure 3.

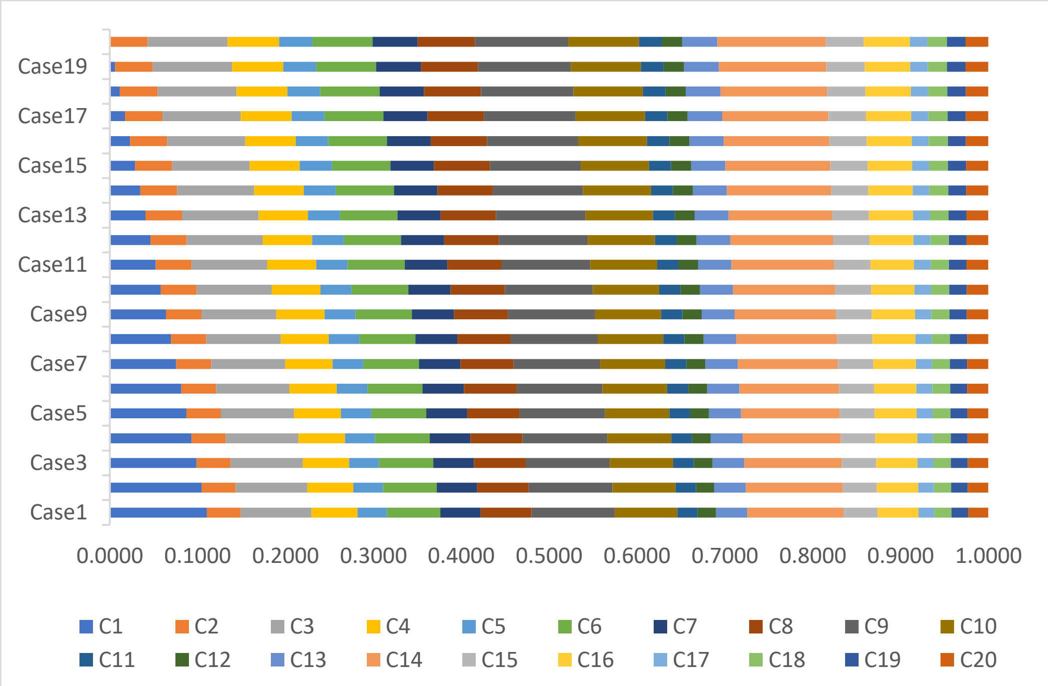

Figure 3. Weights of criteria according to 20 scenarios

The ranking of the airport groups for each scenario is shown in Figure 4. It is observed that only some airport groups (AENA, Fraport, Grupo Aeroportuario) have changed their ranking in the performance ranking for each scenario. This supports the reliability of the proposed model.

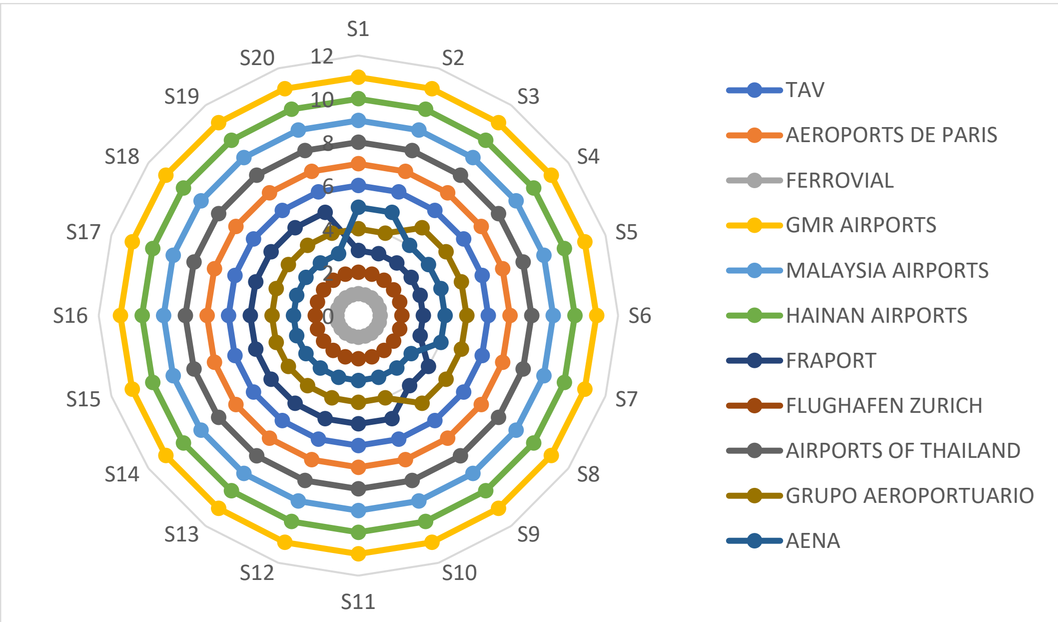

Figure 4. Ranking of airport groups according to 20 scenarios

In the second step of the sensitivity analysis, the results of the proposed model were compared with other MCDM methods (CRADIS, MARCOS, TOPSIS) to support the robustness, applicability and validity of the ranking results obtained by AROMAN method. In this context, CRADIS, MARCOS, and TOPSIS methods were applied to the existing sample. The ranking results of these airport groups for 2023 according to other MCDM methods are presented in Table 3.

Table 3. Aggregated airport groups ranking results for each method

	AROMAN	CRADIS	MARCOS	TOPSIS
TAV	6	9	6	7
AEROPORTS DE PARIS	7	5	9	10
FERROVIAL	**1**	3	2	2
GMR AIRPORTS	11	10	8	9
MALAYSIA AIRPORTS	9	11	10	11
HAINAN AIRPORTS	10	8	11	8
FRAPORT	3	4	4	5
FLUGHAFEN ZURICH	2	**1**	3	**1**
AIRPORTS OF THAILAND	8	7	5	6
GRUPO AEROPORTUARIO	4	2	**1**	3
AENA	5	6	7	4

Table 3 shows that Ferrovial achieved the best performance according to the AROMAN method, Flughafen Zurich ranked highest according to the CRADIS and TOPSIS methods, and Grupo Aeroportuario led according to the MARCOS method. These results support the robustness and applicability of the proposed LOPCOW-AROMAN model. To assess the direction and strength of the relationship between the rankings produced by the proposed model and those from other MCDM methods, a Spearman correlation analysis was conducted. The results of this analysis are presented in Table 4.

Table 4. Spearman correlation results for each method

	AROMAN	CRADIS	MARCOS	TOPSIS
AROMAN	1			
CRADIS	0,845455	1		
MARCOS	0,818182	0,782727	1	
TOPSIS	0,845455	0,827273	0,854545	1

5. Discussion

In this study, the financial performance of airport groups is evaluated in five dimensions (financial structure, liquidity, operational efficiency, profitability and per share values). There are no previous studies in the literature using the MCDM method for the performance analysis of airport groups. Therefore, the findings cannot be directly compared. Therefore, only the results of the study will be discussed in this section. In 2018, the three most important criteria were net income (loss) to operating revenue, working capital to current assets, and operating costs to accounts receivable. In 2019, these shifted to fixed assets to total stockholders' equity, working capital to current assets and income before tax to operating revenue. Notably, the ratio of working capital to current assets remained the second most important criterion in both years. From 2020 onwards, earnings per share became one of the key criteria, reflecting the financial impact of the Covid-19 pandemic. This shift highlights how airport groups began emphasising dividend rates to demonstrate their financial stability to investors. In 2021, the top criteria were net income (loss) to operating revenue, fixed assets to total stockholders' equity and operating costs to accounts payable, indicating a renewed focus on profitability during the pandemic. In 2022, the most important criteria were income before tax to operating revenue, net income (loss) to operating revenue and operating revenue to fixed assets. While the first two relate to profitability, the third reflects operational efficiency, showing that both profitability and operational performance were critical factors in financial performance that year. Finally, in 2023, the key criteria were fixed assets to total stockholders' equity, net income (loss) to operating revenue and operating costs to accounts payable.

Analysing the performance of airport groups, it can be seen that TAV experienced a decline in performance in 2020, but has maintained relatively stable overall performance since then. Malaysia Airports saw a decline in 2021, from which it subsequently recovered. Aéroports de Paris saw a significant drop in performance in both 2020 and 2021, which highlights the substantial impact of the pandemic on financial results. The most dramatic change among the airport groups was seen at Ferrovial, which ranked 10th in terms of financial performance in 2018, but by 2023 had become the best-performing airport group. Conversely, the most notable negative change occurred at Airports of Thailand. Despite being the best-performing airport group in 2018 and 2019, its financial performance weakened considerably following the onset of the pandemic. By 2023, Airports of Thailand had fallen to 8th place in terms of financial performance. This decline is attributed to the lack of geographical diversity of the airports it operates and the slower normalisation of air traffic recovery in the Asia-Pacific region compared to other regions, which likely impacted the group's cash flow negatively during the pandemic.

Another interesting change can be seen in the AENA airport group. While it was the fifth group with the best financial performance in 2018, AENA ranked seventh in 2019. In 2020, AENA was ranked 3rd. Therefore, there is a high degree of variability in AENA's performance ranking. In other words, AENA's financial performance has been highly volatile. Grupo Aeroportuario, on the other hand, is the second-best performing airport group, despite experiencing a decline in financial performance in 2019 and 2022. It experienced a significant decline during the pandemic, followed by a gradual recovery. AENA also experienced a significant decline in 2020, followed by a gradual recovery.

6. Conclusion

This study is pioneering in its application of the LOPCOW based AROMAN performance measurement model to airport groups. The study examines the 2018-2023 period and evaluates the impact of travel restrictions and social distancing practices resulting from the Covid-19 pandemic on the financial performance of airport groups operating in different regions of the world. The Covid-19 pandemic has led to a decrease in operational activities and profitability at airports. In this context, the objective is to assess the financial performance of these airport groups in the pre-pandemic (2018-2019), pandemic (2020-2021) and post-pandemic (2022-2023) periods with MCDM methods.

As a result of the analysis carried out with the LOPCOW method, it is seen that financial structure and profitability ratios have a critical importance for the financial performance of these airport groups. Considering that financial structure and profitability indicators are important for airport groups to survive and continue their operations, this result is not surprising.

The results of the proposed LOPCOW-based AROMAN method reveal the performance of airport companies in the pre-pandemic and post-pandemic period in detail. Furthermore, the findings indicate that there are discrepancies in the relative performance rankings of airport companies during the specified period. For instance, Airports of Thailand demonstrated the most robust financial performance in the pre-pandemic period (2018-2019), followed by Grupo Aeroportuario in the pandemic period (2020), Fraport in the new normal period (2021), and Grupo Aeroportuario and Ferrovial in the post-pandemic period (2022-2023). While Airports of Thailand performed at its optimal capacity in the period preceding the onset of the pandemic (2018-2019), it was determined that there was a decline in performance ranking with the advent of the pandemic, and that these declines persisted in the post-pandemic period. In this context, it can be posited that the company Airports of Thailand is one of those most adversely affected by the Covid-19 pandemic.

It is hypothesised that this study will contribute to the literature on the effects of the Covid-19 pandemic on airport groups. The LOPCOW-based AROMAN method was successfully applied to a sample of 11 airport groups operating in different regions of the world in the study. Consequently, the financial performance of these groups was evaluated. It is hypothesised that the findings will contribute to the financial performance management of airport groups, providing an opportunity for important inferences to be made by airport group managers and air transport sector stakeholders to improve performance during similar crises, such as the one caused by the Covid-19 pandemic.

While this study is widely recognised for its valuable insights into the financial performance of airport groups before and after the Covid-19 pandemic, it is also acknowledged to have certain limitations. Firstly, the study only includes 11 airport groups in its sample. Future research could expand the sample to analyse the financial performance of a larger number of airport groups. Secondly, the analysis focused solely on the financial performance of the companies in question. This is due to the limited availability of data on airport groups. In future studies, operational and environmental criteria of airport groups can be used to evaluate the operational and environmental performance of these companies. Third, MCDM methods measure performance relatively and the performance ranking changes according to the criteria employed. In this respect, future studies can apply different performance measurement methods such as SFA (Stochastic Frontier Analysis), Malmquist TFP (Total Factor Productivity) and DEA (Data Envelopment Analysis) to the existing data set. In this way, more robust results can be obtained regarding the performance of the airport groups in question.

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Appendix

LOPCOW Results

Table 1. Airport groups and abbreviations

CODE	AIRPORT GROUPS
AG1	TAV
AG2	AEROPORTS DE PARIS
AG3	FERROVİAL
AG4	GMR AIRPORTS
AG5	MALAYSIA AIRPORTS
AG6	HAINAN AIRPORTS
AG7	FRAPORT
AG8	FLUGHAFEN ZURICH
AG9	AIRPORTS OF THAILAND
AG10	GRUPO AEROPORTUARIO
AG11	AENA

Table 2. Initial Decision Matrix (2023)

		AG1	AG2	AG3	AG4	AG5	AG6	AG7	AG8	AG9	AG10	AG11
MAX	**C1**	0,53	1,98	0,21	-32,15	0,09	0,53	2,07	1,06	1,37	1,80	1,58
MAX	**C2**	0,31	0,86	0,06	0,77	0,07	0,60	0,77	1,76	2,96	1,32	1,74
MIN	**C3**	0,70	0,73	0,77	0,98	0,64	0,54	0,76	0,45	0,40	0,65	0,55
MAX	**C4**	0,43	0,30	0,19	-0,02	0,55	0,77	0,30	1,22	1,49	0,51	0,79
MAX	**C5**	1,16	0,97	1,21	0,98	0,85	2,33	1,49	1,59	0,82	1,13	1,27
MAX	**C6**	0,62	0,57	0,69	0,45	0,12	0,29	0,21	0,31	0,32	0,73	0,70
MAX	**C7**	0,04	0,36	0,18	-0,03	0,39	0,06	0,36	1,10	0,63	0,82	0,85
MAX	**C8**	0,14	-0,03	0,17	-0,02	-0,18	0,57	0,33	0,37	-0,23	0,12	0,21
MIN	**C9**	14,96	4,41	30,60	7,04	2,75	1,25	7,78	16,14	16,06	4,64	11,14
MİN	**C10**	4,42	3,17	4,63	2,80	5,50	1,91	6,31	3,44	2,68	4,97	3,11
MAX	**C11**	0,27	0,12	0,75	0,03	1,07	0,14	0,07	0,13	0,10	0,42	0,17
MAX	**C12**	0,04	0,05	0,02	0,02	0,03	0,03	0,03	0,08	0,08	0,25	0,11
MAX	**C13**	1,01	1,30	1,36	1,87	1,77	1,22	1,34	1,01	0,97	1,07	1,19
MAX	**C14**	0,98	0,63	0,77	-0,26	0,75	0,56	0,61	0,78	0,60	0,63	0,82
MAX	**C15**	0,04	0,03	0,02	0,00	0,02	0,02	0,02	0,06	0,05	0,16	0,09
MAX	**C16**	0,06	0,05	0,03	-0,01	0,04	0,02	0,02	0,07	0,05	0,18	0,11
MAX	**C17**	4,68	47,41	5,44	-0,02	0,90	0,28	50,11	92,10	0,21	2,30	54,51
MAX	**C18**	0,67	17,40	1,34	-0,01	0,24	0,03	11,47	22,15	0,04	1,17	16,36
MAX	**C19**	0,64	6,86	0,66	0,00	0,06	0,01	4,56	11,08	0,02	1,11	11,65
MAX	**C20**	3,39	59,71	12,43	0,13	0,63	0,08	46,42	45,02	0,09	3,86	36,02

Table 3. Normalized Decision Matrix

		AG1	AG2	AG3	AG4	AG5	AG6	AG7	AG8	AG9	AG10	AG11
MAX	C1	0,95	1,00	0,95	0,00	0,94	0,95	1,00	0,97	0,98	0,99	0,99
MAX	C2	0,09	0,28	0,00	0,24	0,00	0,19	0,25	0,59	1,00	0,43	0,58
MIN	C3	0,48	0,43	0,36	0,00	0,58	0,75	0,38	0,91	1,00	0,56	0,74
MAX	C4	0,30	0,21	0,14	0,00	0,38	0,52	0,21	0,82	1,00	0,35	0,54
MAX	C5	0,23	0,10	0,26	0,11	0,02	1,00	0,44	0,51	0,00	0,21	0,30
MAX	C6	0,81	0,73	0,92	0,54	0,00	0,27	0,15	0,32	0,33	1,00	0,94
MAX	C7	0,06	0,35	0,19	0,00	0,37	0,08	0,35	1,00	0,59	0,75	0,78
MAX	C8	0,46	0,25	0,50	0,25	0,05	1,00	0,69	0,75	0,00	0,43	0,55
MIN	C9	0,53	0,89	0,00	0,80	0,95	1,00	0,78	0,49	0,50	0,88	0,66
MİN	C10	0,43	0,71	0,38	0,80	0,18	1,00	0,00	0,65	0,83	0,30	0,73
MAX	C11	0,23	0,08	0,69	0,00	1,00	0,11	0,04	0,10	0,07	0,38	0,13
MAX	C12	0,11	0,15	0,03	0,00	0,07	0,06	0,08	0,26	0,27	1,00	0,42
MAX	C13	0,05	0,37	0,44	1,00	0,89	0,28	0,42	0,04	0,00	0,12	0,24
MAX	C14	1,00	0,72	0,83	0,00	0,82	0,66	0,70	0,84	0,69	0,72	0,87
MAX	C15	0,28	0,22	0,14	0,00	0,18	0,13	0,15	0,39	0,31	1,00	0,60
MAX	C16	0,37	0,28	0,17	0,00	0,26	0,15	0,17	0,44	0,33	1,00	0,65
MAX	C17	0,05	0,46	0,05	0,00	0,01	0,00	0,49	1,00	0,00	0,02	0,53
MAX	C18	0,03	0,79	0,06	0,00	0,01	0,00	0,52	1,00	0,00	0,05	0,74
MAX	C19	0,06	0,59	0,06	0,00	0,01	0,00	0,39	0,95	0,00	0,10	1,00
MAX	C20	0,06	1,00	0,21	0,00	0,01	0,00	0,78	0,75	0,00	0,06	0,60

Table 4. Percentage Values and (PV_i) and Criteri Weight (W_{ij})

		PV_i	W_{ij}
MAX	C1	114,90441	**0,116094**
MAX	C2	37,75637	0,038147
MIN	C3	79,60590	0,080430
MAX	C4	51,30498	0,051836
MAX	C5	33,00820	0,033350
MAX	C6	59,96365	0,060584
MAX	C7	44,80887	0,045273
MAX	C8	57,23071	0,057823
MIN	C9	93,04815	0,094011
MİN	C10	70,08105	0,070806
MAX	C11	22,71940	0,022955
MAX	C12	20,55130	0,020764
MAX	C13	34,98628	0,035348
MAX	C14	107,77385	0,108889

MAX	C15	38,15905	0,038554
MAX	C16	45,78169	0,046256
MAX	C17	17,43913	0,017620
MAX	C18	19,33704	0,019537
MAX	C19	18,52775	0,018719
MAX	C20	22,76898	0,023005
TOTAL		989,75676	1,000

AROMAN results

Table 5. Linear Normalization Decision Matrix

		AG1	AG2	AG3	AG4	AG5	AG6	AG7	AG8	AG9	AG10	AG11
MAX	C1	0,95	1,00	0,95	0,00	0,94	0,95	1,00	0,97	0,98	0,99	0,99
MAX	C2	0,09	0,28	0,00	0,24	0,00	0,19	0,25	0,59	1,00	0,43	0,58
MIN	C3	0,52	0,57	0,64	1,00	0,42	0,25	0,62	0,09	0,00	0,44	0,26
MAX	C4	0,30	0,21	0,14	0,00	0,38	0,52	0,21	0,82	1,00	0,35	0,54
MAX	C5	0,23	0,10	0,26	0,11	0,02	1,00	0,44	0,51	0,00	0,21	0,30
MAX	C6	0,81	0,73	0,92	0,54	0,00	0,27	0,15	0,32	0,33	1,00	0,94
MAX	C7	0,06	0,35	0,19	0,00	0,37	0,08	0,35	1,00	0,59	0,75	0,78
MAX	C8	0,46	0,25	0,50	0,25	0,05	1,00	0,69	0,75	0,00	0,43	0,55
MIN	C9	0,47	0,11	1,00	0,20	0,05	0,00	0,22	0,51	0,50	0,12	0,34
MİN	C10	0,57	0,29	0,62	0,20	0,82	0,00	1,00	0,35	0,17	0,70	0,27
MAX	C11	0,23	0,08	0,69	0,00	1,00	0,11	0,04	0,10	0,07	0,38	0,13
MAX	C12	0,11	0,15	0,03	0,00	0,07	0,06	0,08	0,26	0,27	1,00	0,42
MAX	C13	0,05	0,37	0,44	1,00	0,89	0,28	0,42	0,04	0,00	0,12	0,24
MAX	C14	1,00	0,72	0,83	0,00	0,82	0,66	0,70	0,84	0,69	0,72	0,87
MAX	C15	0,28	0,22	0,14	0,00	0,18	0,13	0,15	0,39	0,31	1,00	0,60
MAX	C16	0,37	0,28	0,17	0,00	0,26	0,15	0,17	0,44	0,33	1,00	0,65
MAX	C17	0,05	0,46	0,05	0,00	0,01	0,00	0,49	1,00	0,00	0,02	0,53
MAX	C18	0,03	0,79	0,06	0,00	0,01	0,00	0,52	1,00	0,00	0,05	0,74
MAX	C19	0,06	0,59	0,06	0,00	0,01	0,00	0,39	0,95	0,00	0,10	1,00
MAX	C20	0,06	1,00	0,21	0,00	0,01	0,00	0,78	0,75	0,00	0,06	0,60

Table 6. Vector Normalization Decision Matrix

		AG1	AG2	AG3	AG4	AG5	AG6	AG7	AG8	AG9	AG10	AG11
MAX	C1	0,28	3,94	0,04	1033,9	0,01	0,28	4,30	1,13	1,87	3,26	2,49
MAX	C2	0,10	0,74	0,00	0,59	0,00	0,36	0,59	3,10	8,76	1,74	3,01
MIN	C3	0,49	0,53	0,59	0,96	0,42	0,29	0,57	0,20	0,16	0,42	0,30
MAX	C4	0,18	0,09	0,04	0,00	0,30	0,59	0,09	1,49	2,21	0,26	0,63
MAX	C5	1,35	0,95	1,47	0,96	0,72	5,45	2,21	2,52	0,67	1,29	1,61

MAX	C6	0,38	0,32	0,47	0,20	0,01	0,08	0,04	0,10	0,10	0,54	0,49
MAX	C7	0,00	0,13	0,03	0,00	0,15	0,00	0,13	1,22	0,40	0,68	0,72
MAX	C8	0,02	0,00	0,03	0,00	0,03	0,33	0,11	0,14	0,05	0,01	0,05
MIN	C9	223,7	19,42	936,2	49,59	7,57	1,56	60,52	260,59	257,9	21,51	124,04
MİN	C10	19,57	10,05	21,43	7,83	30,2	3,66	39,76	11,83	7,18	24,67	9,64
MAX	C11	0,07	0,01	0,56	0,00	1,14	0,02	0,01	0,02	0,01	0,18	0,03
MAX	C12	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,01	0,06	0,01
MAX	C13	1,03	1,69	1,86	3,49	3,12	1,49	1,80	1,02	0,94	1,16	1,41
MAX	C14	0,96	0,40	0,60	0,07	0,57	0,31	0,37	0,61	0,36	0,40	0,66
MAX	C15	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,01
MAX	C16	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,03	0,01
MAX	C17	21,86	2247,4	29,59	0,00	0,80	0,08	2510,7	10423,5	0,05	5,28	2971,1
MAX	C18	0,45	302,59	1,78	0,00	0,06	0,00	131,56	490,71	0,00	1,36	267,68
MAX	C19	0,41	47,00	0,44	0,00	0,00	0,00	20,81	122,72	0,00	1,23	135,82
MAX	C20	11,47	3564,6	154,4	0,02	0,40	0,01	2154,3	2026,89	0,01	14,90	1297,1

Table 7. Aggregated Averaged Normalization Matrix (β=0.5)

		AG1	AG2	AG3	AG4	AG5	AG6	AG7	AG8	AG9	AG10	AG11
MAX	C1	0,24	0,26	0,24	-0,25	0,24	0,24	0,27	0,25	0,26	0,26	0,26
MAX	C2	0,04	0,12	0,00	0,10	0,00	0,08	0,11	0,25	0,42	0,18	0,24
MIN	C3	0,21	0,23	0,25	0,36	0,18	0,12	0,24	0,07	0,04	0,18	0,13
MAX	C4	0,12	0,09	0,06	0,00	0,16	0,22	0,09	0,34	0,42	0,14	0,22
MAX	C5	0,12	0,08	0,13	0,08	0,05	0,38	0,20	0,22	0,05	0,12	0,15
MAX	C6	0,30	0,27	0,33	0,20	0,02	0,11	0,07	0,13	0,13	0,36	0,34
MAX	C7	0,02	0,14	0,07	0,00	0,15	0,03	0,14	0,40	0,23	0,30	0,31
MAX	C8	0,15	0,05	0,17	0,06	-0,04	0,41	0,27	0,29	-0,06	0,14	0,20
MIN	C9	0,20	0,05	0,42	0,09	0,03	0,01	0,10	0,22	0,22	0,06	0,15
MİN	C10	0,22	0,13	0,24	0,10	0,30	0,04	0,37	0,15	0,09	0,26	0,12
MAX	C11	0,10	0,04	0,30	0,00	0,44	0,05	0,02	0,05	0,03	0,17	0,06
MAX	C12	0,06	0,08	0,03	0,01	0,04	0,04	0,05	0,13	0,13	0,45	0,20
MAX	C13	0,07	0,17	0,19	0,36	0,32	0,14	0,18	0,07	0,06	0,09	0,13
MAX	C14	0,36	0,25	0,29	-0,03	0,29	0,23	0,24	0,30	0,24	0,25	0,31
MAX	C15	0,12	0,09	0,06	0,00	0,07	0,05	0,06	0,17	0,13	0,44	0,26
MAX	C16	0,16	0,12	0,07	-0,01	0,11	0,06	0,07	0,19	0,14	0,43	0,27
MAX	C17	0,02	0,20	0,02	0,00	0,00	0,00	0,22	0,44	0,00	0,01	0,23
MAX	C18	0,01	0,32	0,02	0,00	0,00	0,00	0,21	0,41	0,00	0,02	0,30
MAX	C19	0,02	0,24	0,02	0,00	0,00	0,00	0,16	0,39	0,00	0,04	0,41
MAX	C20	0,02	0,41	0,08	0,00	0,00	0,00	0,32	0,31	0,00	0,03	0,24

Table 8. Aggregated Averaged Weighted Normalized Matrix

		AG1	AG2	AG3	AG4	AG5	AG6	AG7	AG8	AG9	AG10	AG11
MAX	C1	0,03	0,03	0,03	-0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03
MAX	C2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,02	0,01	0,01
MIN	C3	0,02	0,02	0,02	0,03	0,01	0,01	0,02	0,01	0,00	0,01	0,01
MAX	C4	0,01	0,00	0,00	0,00	0,01	0,01	0,00	0,02	0,02	0,01	0,01
MAX	C5	0,00	0,00	0,00	0,00	0,00	0,01	0,01	0,01	0,00	0,00	0,00
MAX	C6	0,02	0,02	0,02	0,01	0,00	0,01	0,00	0,01	0,01	0,02	0,02
MAX	C7	0,00	0,01	0,00	0,00	0,01	0,00	0,01	0,02	0,01	0,01	0,01
MAX	C8	0,01	0,00	0,01	0,00	0,00	0,02	0,02	0,02	0,00	0,01	0,01
MIN	C9	0,02	0,00	0,04	0,01	0,00	0,00	0,01	0,02	0,02	0,01	0,01
MİN	C10	0,02	0,01	0,02	0,01	0,02	0,00	0,03	0,01	0,01	0,02	0,01
MAX	C11	0,00	0,00	0,01	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00
MAX	C12	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00
MAX	C13	0,00	0,01	0,01	0,01	0,01	0,00	0,01	0,00	0,00	0,00	0,00
MAX	C14	0,04	0,03	0,03	0,00	0,03	0,02	0,03	0,03	0,03	0,03	0,03
MAX	C15	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,01	0,02	0,01
MAX	C16	0,01	0,01	0,00	0,00	0,01	0,00	0,00	0,01	0,01	0,02	0,01
MAX	C17	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00
MAX	C18	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,01
MAX	C19	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,01
MAX	C20	0,00	0,01	0,00	0,00	0,00	0,00	0,01	0,01	0,00	0,00	0,01

Table 9. (Li) and (Ai) values and Final Ranking

AIRPORT GROUPS	Li	Ai	λLi	λAi	Ri	RANK
AG1	0,0515	0,13514	0,2268376	0,3676	1,0826	6
AG2	0,0322	0,13953	0,1793413	0,3735	1,0347	7
AG3	0,0765	0,13335	0,2765191	0,3652	1,1301	1
AG4	0,0445	0,00608	0,211033	0,078	0,7386	11
AG5	0,0386	0,1024	0,1965307	0,32	1,009	9
AG6	0,0131	0,14759	0,1142872	0,3842	0,9579	10
AG7	0,0545	0,14491	0,2334215	0,3807	1,1001	3
AG8	0,037	0,20658	0,1922996	0,4545	1,1127	2
AG9	0,0306	0,12274	0,1748178	0,3503	1,01	8
AG10	0,0386	0,18273	0,1965071	0,4275	1,0971	4
AG11	0,0328	0,20283	0,1812288	0,4504	1,0968	5