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EVALUATION OF FINANCIAL AND OPERATIONAL SUSTAINABILITY WITH MULTI-CRITERIA DECISION-MAKING METHODS: AN APPLICATION IN THE US AIRLINE MARKET

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Abstract:
The aim of this study is to investigate the multi-dimensional effects of the Covid-19 pandemic on the sustainability performance of airlines in the U.S. airline market, examine the effect of the Covid-19 pandemic on airline business models, and compare the financial and operational performance of airlines before, during and after Covid-19 pandemic period. In this context, the financial and operational performance of 6 traditional and 5 LCC airlines for the period 2019-2022 was analyzed using the Merec-based Marcos and Cobra methods. First, the financial and operational data for airlines were weighted using the Merec method. Subsequently, using the Marcos and Cobra methods, the financial and operational performance rankings of airlines were determined. According to the rankings obtained through the Marcos and Cobra methods, the airlines with the best performance were American Airlines, Delta Airlines, and Southwest Airlines. Additionally, there was a significant similarity in the performance rankings of all airlines in the sample before and after the Covid-19 pandemic.

Key words: *Covid-19 Pandemic, Financial and Operational Performance, Merec Method, Marcos Method, Cobra Method.*

1. Introduction

The Covid-19 pandemic has led to a sudden decrease in the number of flights in the aviation sector and, consequently, significant losses in passenger revenue for airlines. From this perspective, the Covid-19 pandemic has uniquely impacted the aviation industry. According to the Federal Aviation Administration (FAA) data, the global airline transportation market lost approximately $157 billion in 2020, and the U.S. airline market incurred losses of about $35 billion. The total number of passengers using all airports in the United States in 2020 decreased by more than 60% compared to the previous year, dropping from 935 million to 368 million (FAA, 2023; BTS, 2023).

Airlines have pursued various strategies to mitigate the decline in passenger demand resulting from the Covid-19 pandemic. These strategies can be broadly categorized into three main groups: (1) increasing cash flow, (2) enhancing safety measures, and (3) reducing costs. Among the strategies aimed at increasing cash flow are converting passenger aircraft into cargo planes to accommodate increased cargo flows, repositioning aircraft from business-oriented routes to vacation routes, lowering ticket prices to stimulate demand, securing loans, engaging in lobbying efforts with governments to benefit from tax incentives and subsidies. Strategies related to enhancing safety measures implemented by airlines include improving cabin ventilation systems, keeping middle seats vacant to increase social distancing, mandating the use of face masks on planes, ensuring the use of protective equipment for cabin crew, enhancing aircraft cleaning procedures, making boarding procedures safer, and improving passenger screening measures such as temperature checks and Covid-19 testing. Cost reduction strategies; encompass retiring older and less fuel-efficient aircraft from the fleet, grounding aircraft, implementing salary cuts, and reducing staff (Amankwah-Amoah, 2020; Adrienne et al., 2020; Albers & Rundshagen, 2020; Bauer et al., 2020; Bombelli, 2020; Li, 2020; Czerny et al., 2021; Dube et al., 2021; Milne et al., 2021; Gualini et al., 2023).

Did the strategies implemented by airlines during the Covid-19 pandemic prove to be effective? In this study, The objective of the study is to conduct an analysis to assess the influence of the strategies implemented during the Covid-19 pandemic on the operational performance of airlines operating within the U.S. aviation market. Utilizing financial and operational data from airlines operating in the U.S. aviation market both before the Covid-19 pandemic (2019) and during the pandemic period (2020-2021), as well as in the post-pandemic period (2022), Multi-Criteria Decision Making (MCDM) methods are employed to analyze their financial and operational performance. In this context, this study is believed to contribute to the existing literature.

This article contributes to the growing literature on how the Covid-19 pandemic has affected the aviation industry. Previous research has explored how the Covid-19 pandemic adversely affected the aviation industry through reduced income and decreased demand (Czerny et al., 2021; Lacus et al., 2020; Sanchez et al., 2020). Some studies have focused on the strategies adopted by airlines to cope with the pandemic (Amankwah-Amoah, 2020; Bauer et al., 2020; Czerny et al., 2021). Some studies have examined the impact of the pandemic on airline business models (Kaffash & Khezrimotlagh, 2023; Perez et al., 2022). However, these studies, for example, (Perez et al., 2022) only examined the year 2020, while (Kaffash & Khezrimotlagh, 2023) investigated the period from 2020 to 2021. In this regard, this study, which examines both the pre-pandemic (2019), pandemic (2020-2021), and post-pandemic (2022) periods, is considered distinct from other studies.

The purpose of this study is to examine the impact of the Covid-19 pandemic on the performance of airlines operating in the U.S. aviation market. Additionally, it aims to compare the performance of airlines in the pre-pandemic, pandemic, and post-pandemic periods. In this context, the financial and operational performance of 11 airlines implementing different business models during the period from 2019 to 2022 has been analyzed using the Merec- based Marcos and Cobra methods. In the following sections of the study, Section 2 provides information about the studies in the literature. Section 3 explains the data and methods used. Section 4 examines the findings obtained from the analysis. Finally, in Section 5, the results of the research are evaluated.

2. Literature

2.1. Airline business models

Airline business models are developed over time to adapt to changing market conditions and regulatory environments. The liberalization that began in the United States in 1978 and later spread to other country markets have brought significant changes to the airline transportation industry (Doganis, 2010). These regulations have led to the emergence of new business models, especially Low-Cost Carriers (LCCs). Some key characteristics that distinguish LCC carriers from traditional airlines include the use of a single type of fleet, the utilization of a point-to-point network model instead of the hub & spoke network model, high aircraft utilization rates, and the provision of fee-based services during flights (Magdalina & Bouzaima, 2021). However, due to the dynamic nature of airline transportation, it is not always possible to categorize airline business models into just these two categories. For example, some LCC airlines may adopt some characteristics of traditional airlines, and conversely, some traditional airlines may employ certain strategies used by LCC airlines to become more competitive. In this context, (Mason et al., 2013) have developed an organizational architecture approach that classifies and compares airlines based on their organizational structures and activities. Similarly, (Lohmann & Koo, 2013) have argued that it is unnecessary to classify airlines separately and that airline businesses can simultaneously apply different business models. This idea has led to the emergence of airlines implementing a hybrid business model. (Magdalina & Bouzaima, 2021), in their detailed study on the hybrid business model, classified European airlines into traditional, LCC, and two different hybrid business models. (Bachwich & Wittman, 2017), in their study on the U.S. airline market, mentioned that LCC airlines resemble traditional airlines in some of their practices, leading to the emergence of a new business model called Ultra Low-Cost carriers. Although expressed in different terms, this concept bears a significant resemblance to the definition of a hybrid business model.

2.2. Studies addressing the Covid-19 pandemic in the airline market

Numerous studies have been conducted in the literature to examine the adverse effects of the Covid-19 pandemic on airlines. Some of these studies have focused on the initial period of the Covid-19 pandemic, analyzing the initial responses of airlines (Albers et al., 2020). Additionally, there are studies emphasizing the emergence of new business models in conjunction with the Covid-19 pandemic (Bauer et al., 2020). In the early stages of the pandemic, these studies also highlighted the communication strategies of airlines during the pandemic (Scheiwiller & Zizka, 2021). Other studies have evaluated how to deal with the financial and operational crises that emerged during the Covid-19 pandemic from a management perspective (Amankwah-Amoah, 2020). Some studies have examined the effects of government support provided to the aviation industry during the Covid-19 pandemic (Abate et al., 2020). In certain studies, the impact of the Covid-19 pandemic on the airline market in China and the air cargo market has been investigated (Czerny et al., 2021; Li, 2020). Similarly, a study has explored the impact of the Covid-19 pandemic on the Japanese aviation market (Ng et al., 2022). Budd et al. (2020), investigated the measures taken by European-based airlines during the Covid-19 period. They noted that the most common measures included redesigning flight networks, reducing staff numbers, and streamlining fleets. Yimga (2021), examined the impact of the Covid-19 pandemic on flight delays in the U.S. aviation market. The research found that in the middle of the pandemic period, aircraft experienced fewer delays during takeoff and landing. Maneenop and Kotcharin (2020), conducted research on the stock performance of airlines during the Covid-19 pandemic. The research results indicated that during the early stages of the Covid-19 pandemic, airline stock returns were significantly below the average market returns. In a similar study, Atems and Yimga (2021), examined the stock prices of airlines in the U.S. aviation market during the Covid-19 pandemic. The research concluded that the Covid-19 pandemic had a negative impact on the financial performance of a significant portion of U.S. airlines.

Several studies have explored the impact of the Covid-19 pandemic on both traditional and LCC airlines. For example, Liao et al. (2022), examined the performance of Chinese-based LCC airlines during the Covid-19 pandemic. The research found that LCC airlines were adversely affected by the Covid-19 pandemic. Andreana et al. (2021), conducted macro-level research on the devastating effects of the Covid-19 pandemic. The study concluded that during the Covid-19 pandemic, LCC airlines outperformed traditional airlines. Perez et al. (2022), investigated the impact of the Covid-19 pandemic on American traditional and LCC airlines. The research found that LCC airlines were in a better financial position compared to traditional airlines. Gualini et al. (2023), examined the strategies implemented by American traditional and LCC airlines during the Covid-19 pandemic. The study found that LCCs were better equipped to weather the negative effects of the pandemic due to their stronger position in domestic markets. Kaffash and Khezrimotlagh (2023), researched the impact of the Covid-19 pandemic on the U.S. airline sector. The research concluded that LCC airlines were more efficient compared to traditional airlines. Asker (2023), studied the impact of the Covid-19 pandemic on LCC airlines. The research found that small-scale LCC airlines outperformed medium and large-scale LCC airlines.

3. Data and methodology

In this study, the operational and financial performance of 11 airlines operating in the US airline market, which also apply different business models, is examined, focusing on 9 criteria for the period 2019-2022 using the Merec, Marcos, and Cobra methods. The operational and financial performance criteria included in the study are listed in Table 1.

Table 1. Performance criteria, codes and definitions

Performance Criteria	Type	Code	Definitions (Annual)
Total Passenger	Max	C1	Total number of passengers carried
Total Flights	Max	C2	Total number of flights operated
Revenue Passenger Miles (RPM)	Max	C3	Flight distance X total number of passengers carried for fare
Available Seat Miles (ASM)	Max	C4	Flight distance X number of seats offered for sale
Load Factor	Max	C5	Ratio of revenue passenger mile to available seat mile

Net Income	Max	C6	Net profit amount
Operating Income	Max	C7	The total amount of operating income
Operating Expense	Min	C8	The total amount of operating expenditure
Total Revenue	Max	C9	Total amount of income earned

Operational data related to airlines were obtained from the airlines' annual reports, while financial data were sourced from the Bloomberg database.

Figure 1 presents an flowchart of the Merec-based Marcos and Cobra methods used in the research. In the first step, operational and financial criteria related to the research problem were identified, and then data for these criteria were collected. In the second step, using the Merec method, the weights of the criteria were determined. In the third step, the operational and financial performances of airlines were calculated for each year using the Marcos and Cobra methods. In the final step, the ranking results obtained were compared with other MCDM methods to enhance the validity and reliability of the proposed model.

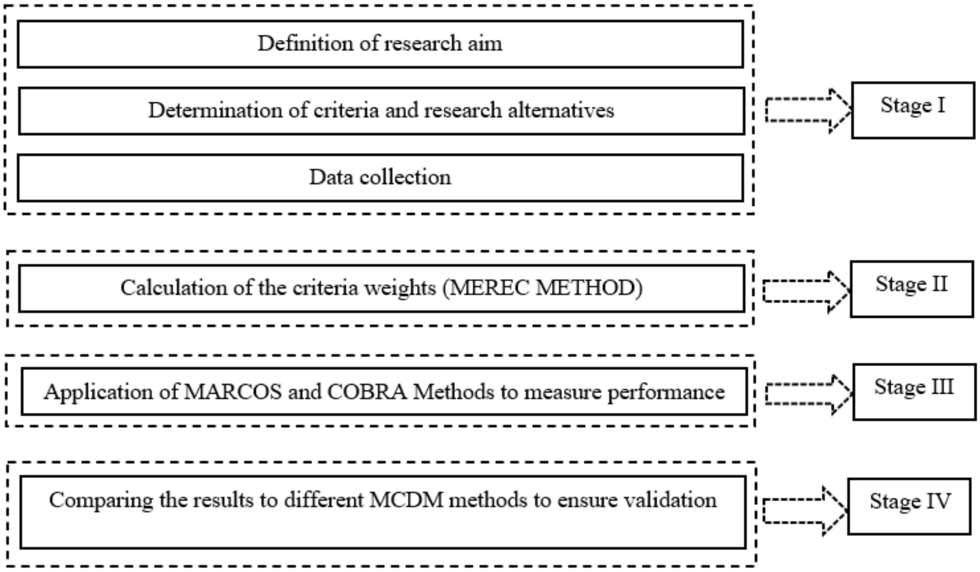

Figure 1. Flow chart of the application model

3.1. Merec (criteria weighting method)

The Merec (Method based on the Removal Effects of Criteria) method is an objective weighting method developed by (Keshavarz-Ghorabae et al. 2021). In the Merec method, when calculating the importance degree of criteria, the specific criterion is excluded from the calculation process, and the focus is on the change in the total criterion weight. The Merec method distinguishes itself from other objective weighting methods in this regard (Haq et al., 2022). The application steps of the Merec method are shown below (Keshavarz-Ghorabae et al. 2021):

Step 1. Organization of the Decision Matrix; To solve the decision problem, the decision matrix consisting of n criteria and m alternatives is organized as shown in Equation (1).

$$Y = [y_{ij}] = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \tag{1}$$

Step 2. Organization of the Normalized Decision Matrix; The evaluation criteria in the decision matrix are normalized based on whether they are benefit (maximum) or cost (minimum) oriented, as shown in Equation (2).

$$n_{ij} = \begin{cases} \dfrac{\min\limits_{i} x_{ij}}{x_{ij}} & , \quad j \in J^{+} \\ \dfrac{\underset{i}{\text{maks}}\, x_{ij}}{x_{ij}} & , \quad j \in J^{-} \end{cases} \tag{2}$$

Step 3. Calculation of Performance Values for Decision Alternatives: In this step of the method, the performance of decision alternatives is calculated using the logarithmic function in Equation (3) to determine the "Si" value.

$$S_i = \ln\left(1 + \left(\frac{1}{n}\sum_j \left|\ln\left(n_{ij}\right)\right|\right)\right) \tag{3}$$

Step 4. Calculation of Performance Value by Subtracting Values for Each Criterion from the Decision Matrix; To calculate the performance for each decision alternative separately for each criterion, the (S'_{ij}) value is calculated using Equation (4) by subtracting values related to the decision matrix.

$$S'_{ij} = \ln\left(1 + \left(\frac{1}{n}\sum_{k,k\neq j} \left|\ln\left(n_{ij}\right)\right|\right)\right) \tag{4}$$

Step 5. Calculation of the Impact Degrees of Removed Criteria in the Decision Matrix; In this step, the value (E_j) representing the impact degree of the removed criterion is calculated using Equation (5).

$$E_j = \sum_i \left|S'_{ij} - S_i\right| \tag{5}$$

Step 6. Calculation of Importance Weights for Criteria; In the final stage of the method, the importance weight values for each criterion are calculated using Equation (6).

$$w_j = \frac{E_j}{\sum_k E_k} \tag{6}$$

3.2. Marcos ranking method

The Marcos (Measurement Alternatives and Ranking According to Compromise Solution) method was introduced to the literature by (Stević et al., 2020). The Marcos method performs the ranking of decision alternatives by defining the relationship between decision alternatives and reference values (ideal and non-ideal alternatives) (Stević & Brković, 2020). In the application process of the method, utility functions for alternatives are determined based on the defined relationships. Then, the ranking of decision alternatives is carried out based on their distances to ideal and non-ideal solutions. Utility functions represent the position of each decision alternative from the perspective of an ideal and non-ideal solution (Stević et al., 2020). As a result, the decision alternative with the best performance is the one that is farthest from the non-ideal reference point and closest to the ideal reference point (Stević & Brković, 2020). Despite having a simple solution algorithm, the Marcos method can be easily applied to solve complex problems (Ecer, 2020). The application steps of the Marcos method are shown below (Stević et al., 2020):

Step 1. The decision matrix, formed by combining decision alternatives and evaluation criteria, is organized as shown in Equation (1).

Step 2. In the second step of the method, ideal (AI) and non-ideal (AAI) solution values are defined, and the initial matrix is expanded as shown in Equation (7).

$$Y = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & & C_n \end{array} \\ \begin{array}{c} AAI \\ A_1 \\ A_2 \\ A_m \\ AI \end{array} & \begin{bmatrix} y_{aa1} & y_{aa2} & \cdots & y_{aan} \\ y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ y_{m1} & y_{m2} & \cdots & y_{mn} \\ y_{ai1} & y_{ai2} & \cdots & y_{ain} \end{bmatrix} \end{array} \tag{7}$$

In Equation (7), (AI) represents the best ideal solution, and (AAI) represents the worst ideal solution. These values are calculated using Equation (8) and Equation (9).

$$\text{AAI} = min_i y_{ij} \ if \ \ j \epsilon B \ ve \ max_i y_{ij} \ if \ j \epsilon C \tag{8}$$

$$\text{AI} = max_i y_{ij} \ if \ \ j \epsilon B \ ve \ min_i y_{ij} \ if \ j \epsilon C \tag{9}$$

In this equation, the cost criterion is denoted as C, and the benefit criterion is denoted as B.

Step 3. In the third step of the method, the expanded initial matrix is normalized based on whether the criteria are benefit-oriented or cost-oriented, as shown in Equation (10) and Equation (11).

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \ \ if \ j \epsilon C \tag{10}$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \ \ if \ j \epsilon B \tag{11}$$

Step 4. In the fourth step of the method, the normalized matrix is weighted by the criterion weight values obtained from the Merec method, as shown in Equation (12), to obtain the weighted normalized decision matrix.

$$V_{ij} = n_{ij} * w_j \tag{12}$$

Step 5. In the fifth step of the method, the benefit degrees (K_i) of decision alternatives are calculated using Equation (13) and Equation (14) based on ideal and non-ideal solutions.

$$K_i^- \frac{S_i}{S_{aai}} \tag{13}$$

$$K_i^+ \frac{S_i}{S_{ai}} \tag{14}$$

The value (S_i) mentioned above represents the sum of the weighted matrix elements for each decision alternative. This value is calculated using Equation (15).

$$S_i = \sum_{i=1}^{m} V_{ij} \tag{15}$$

Step 6. In the sixth step of the method, the benefit functions of decision alternatives $f(K_i)$ are calculated using Equation (16).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{16}$$

In the above formula $f(K_i^+)$) represents the benefit function relative to the ideal solution, while e $f(K_i^-)$ represents the benefit function relative to the non-ideal solution. These functions are obtained using the formulas in Equation (17) and Equation (18).

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{17}$$

$$f(K_i^-) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{18}$$

Step 7. In the final step of the method, decision alternatives are ranked from highest to lowest based on their values of $f(K_i)$ as shown in Equation (16). The decision alternative with the highest $f(K_i)$ value is considered the best-performing decision alternative.

3.3. Cobra ranking method

The Cobra (Comprehensive Distance Based Ranking) method is an MCDM (Multi-Criteria Decision Making) method developed by (Krstic et al., 2022). Due to being a newly developed method, Cobra has been used in a relatively small number of studies (Popoviç et al., 2022); (Krstic et al., 2022). The Cobra method involves a six-step application process. The application steps of the method are as follows (Krstic et al., 2022):

Step 1. The decision matrix, formed by combining decision alternatives and evaluation criteria, is organized as shown in Equation (1).

Step 2. In this step of the method, evaluation criteria are normalized based on whether they are cost-oriented (minimum) or benefit-oriented (maximum) using Equation (19) and Equation (20).

$$[\alpha_{ij}]_{n \times m} \tag{19}$$

$$\alpha_{ij} = \frac{\alpha_{ij}}{max_i \alpha_{ij}} \tag{20}$$

Step 3. In this step, the decision matrix is weighted as shown in Equation (21). The value (w_j) expressed in the formula represents the importance weight value for each criterion obtained from the Merec method's results.

$$\Delta_w = [\omega_j \times \alpha_{ij}]_{n \times m} \tag{21}$$

Step 4. In this step of the method, the values for Negative Ideal Solution (NIS_j), Positive Ideal Solution (PIS_j), and Average Solution (AS_j) for each criterion are calculated using Equation (22-26).

$$PIS_j = max_i(\omega_j \times \alpha_{ij}), \ \forall_j = 1, \ldots\ldots m \ \ za \ j \ni J^B \tag{22}$$

$$PIS_j = min_i\ (\omega_j \times \alpha_{ij}),\ \ \forall_j = 1, \ldots\ldots m\ \ za\ j \ni J^C \quad (23)$$

$$NIS_j = min_i\ (\omega_j \times \alpha_{ij}),\ \ \forall_j = 1, \ldots\ldots m\ \ za\ j \ni J^B \quad (24)$$

$$NIS_j = max_i\ (\omega_j \times \alpha_{ij}),\ \ \forall_j = 1, \ldots\ldots m\ \ za\ j \ni J^C \quad (25)$$

$$AS_j = \frac{\sum_{i=1}^{n}(\omega_j \times \alpha_{ij})}{n}\ \ \forall_j = 1, \ldots\ldots m\ \ za\ j \ni J^B, J^C \quad (26)$$

Step 5. In this step, the values for positive ideal solution ($d(PIS_j)$), negative ideal solution ($d(NIS_j)$), positive distance from average solution ($d(AS_j)_i^+$), and negative distance from average solution ($d(AS_j)_i^-$) are calculated using Equation (27).

$$d(S_j) = dE(S_j) + \partial \times dE(S_j) \times dT(S_j)\ \ \forall_j = 1, \ldots\ldots m, \quad (27)$$

The value (S_j) represents the values belonging to $(NIS_j, PIS_j, AS_j)'$) and (∂) is calculated using the formula in Equation (28).

$$\partial = max_i\ dE(S_j) - min_i\ dE(S_j), \quad (28)$$

Positive ideal solution's Euclidean distances representing the function $dE(S_j)$ are calculated using Equation (29).

$$dE(PIS_j)_i = \sqrt{\sum_{j=1}^{m}(PIS_j - \omega_j \times \alpha_{ij})^2}\qquad \forall_i = 1, \ldots\ldots, n,\ \ \forall_j = 1, \ldots\ldots, m, \quad (29)$$

Taxicab distances representing the function $dT(S_j)$ for positive ideal solution are calculated using Equation (30).

$$dT(PIS_j)_i = \sum_{j=1}^{m}|PIS_j - \omega_j \times \alpha_{ij}|\qquad \forall_i = 1, \ldots\ldots, n,\ \ \forall_j = 1, \ldots\ldots, m, \quad (30)$$

Euclidean distances for negative ideal solution are calculated using Equation (31).

$$dE(NIS_j)_i = \sqrt{\sum_{j=1}^{m}(NIS_j - \omega_j \times \alpha_{ij})^2}\qquad \forall_i = 1, \ldots\ldots, n,\ \ \forall_j = 1, \ldots\ldots, m, \quad (31)$$

Taxicab distances for negative ideal solution are calculated using Equation (32).

$$dT(NIS_j)_i = \sum_{j=1}^{m}|NIS_j - \omega_j \times \alpha_{ij}|\qquad \forall_i = 1, \ldots\ldots, n,\ \ \forall_j = 1, \ldots\ldots, m, \quad (32)$$

Positive distance from the average solution's Euclidean and Taxicab distances are calculated using Equation (33-35), respectively.

$$dE(AS_j)_i^+ = \sqrt{\sum_{j=1}^{m}\tau^+(AS_j - \omega_j \times \alpha_{ij})^2}\ \ \forall_i = 1, \ldots\ldots, n,\ \ \forall_j = 1, \ldots\ldots, m, \quad (33)$$

$$dT(AS_j)_i^+ = \sum_{j=1}^{m}\tau^+|AS_j - \omega_j \times \alpha_{ij}|\qquad \forall_i = 1, \ldots\ldots, n,\ \ \forall_j = 1, \ldots\ldots, m, \quad (34)$$

$$\tau^+ = \begin{cases} 1 & if\ AS_j < \omega_j \times \alpha_{ij} \\ 0 & if\ AS_j > \omega_j \times \alpha_{ij} \end{cases}, \quad (35)$$

Negative distance from the average solution's Euclidean and Taxicab distances are calculated using Equation (36-38), respectively.

$$dE(AS_j)_i^- = \sqrt{\sum_{j=1}^{m}\tau^-(AS_j - \omega_j \times \alpha_{ij})^2}\ \ \forall_i = 1, \ldots\ldots, n,\ \ \forall_j = 1, \ldots\ldots, m, \quad (36)$$

$$dT(AS_j)_i^- = \sum_{j=1}^{m}\tau^-|AS_j - \omega_j \times \alpha_{ij}|\qquad \forall_i = 1, \ldots\ldots, n,\ \ \forall_j = 1, \ldots\ldots, m, \quad (37)$$

$$\tau^{-} = \begin{cases} 1 \ if \ AS_j > \omega_j \times \alpha_{ij} \\ 0 \ if \ AS_j < \omega_j \times \alpha_{ij} \end{cases}, \quad (38)$$

Step 6. In the final step of the method, the values for decision alternatives (dC_i) are calculated using Equation (39).

$$dC_i = \frac{d(PIS_j)_i - dE(NIS_j)_i - d(AS_j)_i^{+} + dT(AS_j)_i^{-}}{4} \qquad \forall_i = 1, \ldots\ldots, n, \quad (39)$$

4. Results

In this section, the financial and operational performance of both traditional and LCC airlines operating in the US airline market before the Covid-19 pandemic (2019), during the pandemic period (2020-2021), and after the pandemic (2022) is examined using the Merec-based Marcos and Cobra methods. To enhance the reliability and validity of the results obtained, the results were compared with other MCDM (Multi-Criteria Decision Making) models. Within the scope of the research, we compared the financial and operational performance of 11 airlines for the period 2019-2022.

4.1. Merec results

In this step, the weights of the criteria in the initial decision matrix for airlines were determined using the Merec method. The decision matrix consists of values for each alternative and for each criterion. In this study, 11 × 9 decision matrix was created for each year from 2019 to 2022. When looking at Table 2, one can observe the changes in the weights of the criteria both over time and within themselves. It is evident that the criterion with the highest weight throughout the period 2019-2022 is load factor. The criterion with the lowest weight varied from year to year (Total passengers in 2020 and Net income in 2019 and 2021-2022).

Table 2. Merec method performance criteria weight (2019-2022)

Year	C1	C2	C3	C4	C5	C6	C7	C8	C9
2019	0,0762	0,0796	0,1023	0,1012	**0,2579**	0,0321	0,1055	0,1396	0,1057
2020	0,0619	0,0957	0,0833	0,0830	**0,2834**	0,0666	0,1018	0,1208	0,1035
2021	0,0631	0,0879	0,0949	0,1012	**0,2691**	0,0465	0,1128	0,1122	0,1123
2022	0,0747	0,0612	0,1142	0,1135	**0,2632**	0,0454	0,1170	0,0931	0,1178

4.2. Marcos and Cobra ranking results

After calculating the weight values of criteria for airlines using the Merec method, in this step, the financial and operational performances of airlines were examined using the Marcos and Cobra methods. The performance rankings of airlines for the period 2019-2022 according to the Marcos and Cobra methods are presented in Table 3.

Table 3. Ranking results of airlines obtained from Marcos and Cobra method

	2019		2020		2021		2022	
Airlines	**Marcos**	**Cobra**	**Marcos**	**Cobra**	**Marcos**	**Cobra**	**Marcos**	**Cobra**
American Airlines	2	2	3	3	**1**	2	2	2

Alaska Airlines	9	7	**11**	8	8	7	9	7
Allegiant Airlines	6	**11**	8	10	10	**11**	7	**11**
Delta Airlines	**1**	**1**	2	2	2	**1**	**1**	**1**
Frontier Airlines	8	5	7	6	9	5	10	5
Hawaiian Airlines	**11**	10	9	9	**11**	10	**11**	10
Jetblue Airways	7	6	10	7	6	6	6	6
Skywest	5	8	6	5	5	8	5	8
Southwest Airlines	4	4	**1**	**1**	3	4	4	4
Spirit Airlines	10	9	5	**11**	7	9	8	9
United Airlines	3	3	4	4	4	3	3	3

According to the rankings based on the Marcos method, it is determined that Delta Airlines had the best performance in 2019 and 2022, Southwest Airlines in 2020, and American Airlines in 2021. It is also found that Hawaiian Airlines had the worst performance in 2019 and 2021-2022, and Alaska Airlines in 2020 according to the Marcos method. According to the results of the Cobra method, Delta Airlines had the best performance in 2019 and 2021-2022 and Southwest Airlines in 2020, while Allegiant Airlines had the worst performance in 2019 and 2021-2022, and Spirit Airlines in 2020.

The results of the recommended Merec-based Marcos and Cobra models comprehensively present the performance rankings of the included airlines for the period from 2019 to 2022. However, it also demonstrates changes in the financial and operational performance of the airlines in the sample during the pre-Covid-19 (2019) and pandemic period (2020-2021). Nevertheless, in the pre-pandemic (2019) and post-pandemic period (2022), a significant similarity is observed in the performance rankings of all airlines. This can be interpreted as an indication that these airlines largely overcame the adverse effects of the Covid-19 pandemic in the year 2022.

During the Covid-19 pandemic in 2020-2021, Delta Airlines saw a decline in its performance and slipped from the first position to the second. However, as the impact of the Covid-19 pandemic diminished, the airline's performance improved, and it regained the first position. Similarly, American Airlines, Alaska Airlines, Jet Blue Airways, and United Airlines were also adversely affected by the Covid-19 pandemic, resulting in a drop in their rankings. It has been observed that the performance of these airlines increased again in the post-pandemic period (2022). Some airlines, on the other hand, felt the negative effects of the Covid-19 pandemic to a lesser extent. For example, it was observed that the performance of Southwest Airlines improved during the pandemic. Possible reasons for this include Southwest Airlines conducting a significant portion of its flights on domestic routes during the pandemic.

The analysis results indicate that large-scale traditional airlines (Delta Airlines, American Airlines, United Airlines) outperformed small-scale traditional airlines (Alaska Airlines, Hawaiian Airlines, Skywest). Possible reasons for this include strategies employed by large-scale traditional airlines such as middle-seat blocking, as mentioned in (Gualini, Zou, & Dresner, 2023). Similarly, large-scale LCC airlines (Southwest Airlines) performed better than small-scale LCC airlines (Allegiant Airlines, Frontier Airlines, Jetblue Airways, Spirit Airlines).

4.3. Validation

In this step, to test the validity and reliability of the model applied and to obtain ranking results with the Marcos and Cobra methods, a comparison was made between the results of the model and other MCDM (Multi-Criteria Decision Making) methods. In this context, the Mabac method (Pamucar & Cirovic, 2015), Codas method (Keshavarz Ghorabaee et al., 2016), and Waspas method (Zavadskas et al., 2012) were applied to the current sample. Subsequently, ranking results for airlines for the 2019 year were determined according to all MCDM methods. The ranking results obtained according to the MCDM methods are shown in Table 4.

Table 4. Airlines ranking result for each comparison method overall years (2019)

Aırlınes	Marcos	Cobra	Mabac	Codas	Waspas
American Airlines	2	2	**1**	2	2
Alaska Airlines	9	7	10	11	5
Allegiant Airlines	6	**11**	8	5	10
Delta Airlines	**1**	**1**	3	**1**	**1**
Frontier Airlines	8	5	6	8	9
Hawaiian Airlines	**11**	10	11	6	11
Jetblue Airways	7	6	7	10	6
Skywest	5	8	9	7	8
Southwest Airlines	4	4	2	4	4
Spirit Airlines	10	9	5	9	7
United Airlines	3	3	4	3	3

According to Table 4, Delta Airlines and American Airlines are seen to have the best performance for the 2019 year according to 5 different MCDM methods. Moreover, despite some minor differences, similar ranking results were generally obtained in all 5 different methods. These results support the validity and reliability of our proposed model. Additionally, to reveal the strength and direction of the relationship between our proposed model and other MCDM methods, the Spearman correlation was conducted. The Spearman correlation results for 5 different MCDM methods are presented in Table 5.

Table 5. Spearman's correlation coefficient of different MCDM methods results

	Marcos	Cobra	Mabac	Codas	Waspas
Marcos	1	0,6818	0,8181	0,8909	0,6545
Cobra	0,6818	1	0,745455	0,5272	0,9309
Mabac	0,8181	0,7454	1	0,6727	0,7818
Codas	0,8909	0,5272	0,6727	1	0,5590
Waspas	0,6545	0,9309	0,7818	0,5590	1

According to the correlation results in Table 5, there is a positive and strong correlation among the 5 different MCDM methods. This finding supports the validity and reliability of the results obtained with our proposed Marcos and Cobra methods.

5. Conclusion and discussion

In this study, the disruptive impact of the Covid-19 pandemic crisis on the performance of airlines in the U.S. airline market was investigated. Additionally, the effects of travel restrictions implemented during the Covid-19 pandemic on the sustainable performance of these airlines were examined. The financial and operational performance of airlines before and after the pandemic was also compared. Finally, the impact of the Covid-19 pandemic on airline business models was explored. In this context, the financial and operational performance of 11 airlines in the U.S. airline market for the period 2019-2022 was analyzed using the Merec-based Marcos and Cobra methods.

In the first step of the analysis, financial and operational data for airlines were weighted using the Merec method. According to the results of the Merec method, the load factor variable had the greatest weight on the performance of both traditional and LCC airlines before and after the pandemic. Since the load factor is assumed to be a crucial variable for airline success, this result was expected. In the second step of the analysis, the financial and operational performance rankings of traditional and LCC airlines were determined using the Marcos and Cobra methods. According to the results of the Marcos and Cobra methods, Delta Airlines, Southwest Airlines, and American Airlines were found to have the best performance. The possible reasons for Delta Airlines and American Airlines having top-tier performance may include their implementation of the middle-seat blocking strategy in 2020-2021, as mentioned in (Gualini et al., 2023). Southwest Airlines' strong performance in 2020 may be attributed to a significant portion of its flights being operated on domestic routes.

According to the results of the recommended Merec Based Marcos and Cobra methods, a decrease in performance was observed in American Airlines, Alaska Airlines, Delta Airlines, Jetblue Airways, and United Airlines during the impactful year of 2020 due to the Covid-19 pandemic. Possible reasons for this situation may include a reduction in the operational revenues of these airlines and a disruption in their liquidity structures. However, Southwest Airlines experienced an increase in performance during this period. Possible reasons for this improvement in performance for Southwest Airlines could be attributed to its focus on local flight networks (Gualini, Zou, & Dresner, 2023). Additionally, the findings indicate that a significant portion of these airlines had performance levels post-Covid-19 pandemic (2022) that were very close to their pre-pandemic levels (2019). This could be interpreted as these airlines quickly overcoming the adverse effects of the Covid-19 pandemic.

Based on the results of the Merec-based Marcos and Cobra methods, it was observed that there were performance declines in American Airlines, Alaska Airlines Delta Airlines, Jetblue Airways, and United Airlines during the year 2020, which was heavily affected by the Covid-19 pandemic. On the other hand, Southwest Airlines showed improved performance during this period. The likely reasons for this could be these airline' focus on local flight networks, as mentioned in (Gualini et al., 2023).

According to the analysis results, some large-scale traditional airlines (Delta Airlines, American Airlines) outperformed both small-scale traditional airlines (Alaska Airlines, Hawaiian Airlines, Skywest) and LCC airlines (Allegiant Airlines, Frontier Airlines, Jetblue Airlines, Spirit Airlines) during the period 2019-2022. These findings contradicted the results of the studies conducted by (Kaffash & Khezrimotlagh 2023) and Perez et al. (2022), which may be attributed to the different variables used in the analysis.

This study investigates how different types of airlines responded to the crisis caused by the Covid-19 pandemic. Additionally, it evaluates the financial and operational performance of airlines employing different business models during unexpected crisis periods such as the Covid-19 pandemic. Despite variations in the performance of airlines during this period, it is known that the aviation industry as a whole experienced significant losses. Adequate resources and time are required to recover from these losses. Considering that industries with high sensitivity to external shocks, such as the aviation sector, operate with low-profit margins and are considered economically sustainable in the long term, the continuation of their operations is often dependent on subsidies provided by the government (Hotle & Mumbower, 2021). In this context, it is believed that subsidies provided by the government in the American aviation transportation market positively impact the financial and operational performance of airlines. The analysis results indicate that the performance rankings of these airlines in the post-pandemic period (2022) are close to their rankings in the pre-pandemic period (2019), supporting this notion.

In previous studies, varying opinions have been observed regarding the performance of traditional and Low-Cost Carrier (LCC) airlines during the Covid-19 pandemic. Some studies emphasize that traditional airlines received more government support compared to LCC airlines (Abate et al., 2020), while other studies claim that LCC airlines, due to their flexible structures, exhibited better financial and operational performance during crisis periods (Perez et al., 2022; Sun, Wandelt, & Zhang, 2022; Kaffash & Khezrimotlagh, 2023). In this study, the financial and operational performance of traditional and LCC airlines in the USA was evaluated using Multiple Criteria Decision Making (MCDM) methods. The analysis results indicated that large-scale traditional airlines (Delta Airlines, American Airlines) and LCC airlines (Southwest Airlines) exhibited better performance. The study by Gualini, Zou, & Dresner (2023) highlighted Delta Airlines' successful implementation of the middle-seat blocking strategy, leading to increased returns. They also noted that Southwest Airlines, during the pandemic, focused on expanding its local flight networks, resulting in enhanced yields. Similarly, the study found that American Airlines maintained a higher load factor by leveraging regional carriers. In this regard, this study aligns with the findings of Gualini, Zou, & Dresner (2023), supporting the outcomes of their research.

It is believed that this study, utilizing the Merec-based Marcos and Cobra methods, contributes to the growing literature on how the Covid-19 pandemic has affected the aviation industry. Furthermore, it provides stakeholders in the aviation sector with information about the financial and operational performance of airlines operating in the U.S. airline market. However, the study has some limitations, including the relative nature of the MCDM methods used to measure performance, the potential for performance rankings to change based on the variables included in the analysis, a focus on a specific market, the inclusion of only passenger airlines in the sample, and the examination of performance solely from financial and operational perspectives. Future studies could encompass a broader range of airline markets, including both passenger and cargo carriers, and evaluate performance from multiple perspectives.

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