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Critical limit assessment and optimization of airline fleet service strategy

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ABSTRACT

Given the recent changes in the world, it is fair to say that there have been many changes in air transport. It is a fact that there is a great intensity of demand in the civil aviation sector, especially with the increasing demand for fast transportation trends. On the other hand, reasons such as the pandemic that affected the whole world and the disruption of air transportation made operations expensive, affecting operations on a sectoral basis and the world economy. It is known that although many airlines went bankrupt under these conditions, new airlines were also founded. In this study, a fleet analysis using the Response Surface Methodology and the Load factor Profitability Rate is conducted to examine the purposes of the existing airlines' fleet structures and what is required to build a fleet. The main reason for all these discussions is to show the most realistic parameters and limits to ensure the economic sustainability of airlines. The Response Surface Methodology was used for fleet analysis and optimization for the first time in the literature.

1. Introduction

The civil aviation industry is the common denominator of many institutions and organizations, especially airlines, civil aviation authorities, airports, and aircraft manufacturers. One of the most important players among these organizations is considered to be the airlines. Defining airlines by dividing them into groups according to their business models is possible. This grouping is based on how airlines generate revenue, the products they offer, the value they add to the service they provide, their revenue streams, and the customer profile they appeal to. Liberalization and competition among companies allow each competing company to determine its business model relative to its competitors.

Most of the strategic decisions airlines will make over the long term start with fleet planning. The fleet planning process is followed by the route planning and tariff planning processes. Therefore, accurate fleet planning is also important for airlines to make their long-term strategic decisions well. Airline fleet planning involves inputting data from many different sources within an airline. Key data include passenger traffic, revenue, aircraft efficiency, and estimated operational costs. With the synthesis of all these data inputs, the output of the assessment is determined. For many airlines, these forecasts are generated through various databases created by different departments, and the airline decision-making processes are idealized. The steps in these decision-making processes are shown in Fig. 1 below (Belobaba et al., 2015).

Fleet planning is simply a matter of answering the question of which aircraft to accrue and how many. Since the purchase or lease of an aircraft requires a very high investment cost, the selection of the appropriate aircraft is the decisive factor in the success or failure of an airline. As far as the evaluation process is concerned, the most important factor for a network is the expected number of passengers and the value of this number in terms of paid passenger kilometers. To determine this number, a paid passenger estimate study is conducted. When an estimate of future paid passenger miles is made, the 'average occupancy rate' factor is used to determine the required seat mileage. Passenger occupancy rate is the ratio of paid passenger kilometers to seat kilometers offered, a hypothetical ratio assumed at this stage based on estimates and observations.

Based on assumptions about the efficiency of the aircraft type in terms of the seat kilometers it can produce on a daily, monthly, or annual basis, the number of aircraft required to achieve the target seat kilometers to be offered in the future can be calculated. Aircraft added to the fleet; mutual funds will also have financial implications, such as depreciation value and interest rates. At the same time, analysis of estimated operating costs for aircraft types can complicate estimates of operating costs and financial impacts. The estimated revenue from the new aircraft is based on both the initial estimates of passenger numbers to decide on the number of aircraft needed and the estimates of paid passenger miles the airline expects to earn on the routes where the

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Fig. 1. Airline decision-making process (Belobaba et al., 2015).

aircraft will be used. Combining revenue estimates with operating cost estimates gives airlines the ability to forecast operating profits or set profit targets for the aircraft type. These estimates are used to make predictions about how airlines' balance sheets and cash flow statements will be impacted (Belobaba et al., 2015).

An Airline may wish to radically reorganize its fleet, or it may purchase one or two aircraft for a particular route to be used in its operations. In either case, the evaluation process is supported by one of two approaches to measuring the economic and financial impact of alternative aircraft.

1) Top-down or 'macro' approach, based on relatively highly aggregated analyses;
2) Bottom-up or 'micro' approach based on forecasts and detailed analysis of data by flight and route.

In the macro approach to fleet planning evaluation, combined demand and cost tables are used to evaluate the financial impact of selected aircraft options given a subsystem, region, or route. (Load Factor, paid passenger-kilometer, cost per seat, etc.) The capacity gap is defined as the gap between the available seat kilometers that will be needed in the future and the available seat kilometers and the seat kilometers that are negative due to currently available seat kilometers and aircraft to be removed from service.

In cases where the airline's future capacity gap can be met by various types of aircraft, it may be necessary to use aircraft with different specifications for various routes, different flight lengths, and demand forecasts. To measure 'aircraft efficiency' the unit of seat-kilometers provided per day, the required number of aircraft is calculated, considering assumptions about the average flight service time and the average daily flight time of the aircraft. To compare the economic performance of different types of aircraft, the estimation of aircraft operating costs can also be based on aircraft manufacturer ratings or historical data. In addition to this information, it is also a fact that the aviation sector is more fragile than other sectors due to factors such as possible wars, terrorism, political interventions, economic crises, and embargoes. Therefore, uncertainty is a concept that should always be considered by airline managers. Since fleet planning is a long-term strategic move, it should be considered normal to make some concessions due to unpredictable factors that may arise in the future.

2. Literature review

Numerous techniques are used in the study of airline efficiency and fleet analysis, including multi-criteria decision-making techniques (MCDM), stochastic frontier analysis (SFA), DEA, Tobit, logit, and other regression models.

The first set of studies (Barros & Wanke, 2015; Dinçer et al., 2017; Pineda et al., 2018; Wang & Luo, 2006; Wanke et al., 2015; Shojaei et al., 2018) used MCDMs to study airline performance. The conclusions of these studies were obtained with the help of various MCDMs. The main problem is that MCDM methods often require detailed knowledge of the scores and weights of the attributes used for evaluation. In addition, different results may be obtained due to different areas of competence and experience, even if different specialists use the same procedure. However, the ranking depends heavily on the weighting of the attributes. Finally, different MCDMs, even when applied to the same data, may produce different results. There is no dominant MCDM technique, which makes it difficult to find a more effective MCDM strategy for assessing airline performance (Wang et al., 2016). SFA and DEA are the basis of another study. The DMU is assumed to be inefficient and outside the efficiency frontier of DEA. SFA assumes that this deviation departure from the efficiency frontier could be due not only to inefficiency but also to random influence. Lee and Worthington (2014); Lu et al. (2014); Mallikarjun (2015); Saranga and Nagpal (2016); and Rouse et al. (2002); are some examples of studies that focus on a particular area or nation in terms of airline performance analysis. A recent trend (Arjomandi & Seufert, 2014; Chang et al., 2014; Choi et al., 2015; Cui & Li, 2017) uses DEA models to evaluate financial and environmental performance.

There is no consensus in the current literature on whether SFA or DEA are appropriate for evaluating airline efficiency (Coli et al., 2007). However, the DEA has several advantages. It considers a wide range of inputs and results. It is user-friendly because it is based on linear programming. Moreover, it makes no assumptions about the statistical properties of the variables or the functional structure that connects the inputs and outputs. In this way, the wrong function can be prevented from being used. Furthermore, according to Retzlaff-Roberts et al. (2004), DEA enables the identification of efficiency targets that help improve the performance of underperforming DMUs and point out areas that need improvement. Because of these benefits, they are widely used to assess airport and airline efficiency (e.g., Barros & Couto, 2013; Barros & Peypoch, 2009; Coli et al., 2011; Ha et al., 2013; Yang & Huang, 2014).

On the other hand, there are various efforts to introduce new model tests and their effects into the literature. For this reason, the Response Surface Methodology was used for fleet analysis, for which there are no examples in the literature yet. In the study on RSM, which is used in the review of literature in many fields, classifications of the method are made according to the fields in which it is used (Hadiyat et al., 2022). For more information, please refer to the corresponding article. The classification of the studies performed in this study is shown in Table 1.

As can be seen from the above table, while there are no industrial engineering applications among the application areas, many of the studies conducted include relational analysis and response analysis, which were found to be useful.

3. Research design

In this study, Response Surface Methodology (RSM) and Break-Even Load Factor (BELF) are used in tandem to provide a robust analysis

Table 1
Distribution of studies according to research fields (Hadiyat et al., 2022).

Field of Application of RSM	Percentage
pharmacy/chemistry/chemical engineering	22.50 %
manufacturing process	18.75 %
petroleum/coal/mining	11.25 %
cleaner production/waste	10.00 %
material & mechanical engineering	7.50 %
energy	6.25 %
food	5.00 %
civil engineering	3.75 %
medical science	3.75 %
aerospace	2.50 %
biology	2.50 %
methodological development	2.50 %
waste processing	2.50 %
social science	1.25 %

framework for fleet management under evolving global conditions, particularly post-COVID-19. The combination of these tools is essential to capture both the optimization potential and the economic feasibility of fleet operations in uncertain times.

RSM is a statistical technique that enables the modeling and optimization of complex processes with multiple interacting variables, such as fuel costs, demand fluctuations, and operational constraints. In the context of fleet management, RSM allows us to examine how various operational factors and external conditions influence cost efficiency, safety, and overall profitability. By using RSM, this paper systematically explores different operational scenarios to find optimal conditions that maximize profitability while adapting to global uncertainties. On the other hand, BELF represents the minimum load factor required for an airline to break even, essentially a benchmark for operational viability. BELF analysis in this study provides an economic perspective, helping to assess the feasibility of different fleet configurations and route planning strategies identified through RSM. By calculating BELF across different scenarios, we can determine whether the optimized configurations from RSM are sustainable under varying levels of passenger demand and revenue changes, which are particularly sensitive post-COVID-19. By combining RSM with BELF, this study not only identifies optimal fleet management strategies but also ensures their economic sustainability. RSM allows us to test the impact of various operational adjustments, while BELF provides a clear threshold to gauge the economic viability of these adjustments. Together, these methods enable a comprehensive approach to fleet management that is both performance-oriented and grounded in economic reality, offering insights into how airlines can adapt to the dynamic aviation environment effectively.

3.1. Break-even load factor

Aircraft capacity efficiency can be measured by aircraft load factor (LF) (Vasigh et al., 2015). For airlines, the indicator LF is one of the factors that determine profitability. When LF increases, operating revenues increase and have a positive impact on airline profitability. This indicator is one of the factors affecting capacity utilization and airline profitability. At the same time, increasing aircraft LF puts pressure on profitability, growth, and airlines to buy or lease aircraft (Wensveen, J. G., 2011). Using innovative revenue management systems to analyze flight operations, LF has become a critical performance metric worthy of scrutiny.

Airline operating costs are expressed as cost per available seat kilometer (CASK). RASK is expressed as unit revenue, while CASK is expressed as unit cost. An airline's operating profit is derived from the relationships between these indicators (Bood & Ison, 2017). The group of profitability ratios, which also indicates a company's performance ratios, reflects the company's ability to generate a profit from sales, assets, and equity, but also shows how well its resources are being used to create the company's equity value. The long-term profitability of a company increases both the continuity of the company and the attractiveness of the company to shareholders and investors. In this vein, the relationship between the CASK metric and the stock price is measured, as is its potential to be a performance-determining factor for airlines. Another important metric that indicates airline operating profitability is the Breakeven Load Factor (BELF). If the BELF ratio is lower than the LF ratio, there is an operating profit, while if the LF ratio is higher than the BELF, there is an operating loss (Vasigh et al., 2015).

In a comprehensive study, Francis et al. (2005) classified non-financial performance indicators for airlines into three categories. These are operational performance indicators, environmental indicators, and service quality indicators. In addition, Gudmundsson (2002) classified non-financial indicators into six categories in his study. These are operations management, information communication, external environmental impact, management and organization, financial management, and marketing management. In this study, some of the non-financial operational indicators are discussed based on the findings of Francis et al. (2005). These are RPK, LF, and CASK variables shown in Table 2.

In this section shown in Table 2, BELF could be determined with two variables which are;

1) Unit costs (operating expenses resulting per available seat kilometers (or miles))
2) Passenger yield (passenger revenue which results per revenue passenger kilometers (or miles))

Computation of Break-Even Load Factor is shown in Eq. (1);

$$BELF = \frac{Unit\ cost}{Passenger\ Yield} \tag{1}$$

The calculation of the Break-Even Load Factor (BELF) is crucial for analyzing the current and future fleet of airlines since the investment rate and turnover time have to be estimated. For this purpose, BELF is calculated using some internationally operating airlines that are representative of all service types that can be counted as Full-Service Carriers (FSC), Low-Cost Carriers (LCC), and Ultra Low-Cost Carriers (ULCC). For the calculation of the Brek Even Load Factor, the period from 2010 to 2020 was chosen, covering the outbreak of COVID-19 (See Fig. 2).

Looking at Fig. 2, it is clear that the FSC representatives, unlike the LCC representatives, have had a wide range of escalations over the years. This situation is the main question of this study. Is there an impact of an airline's fleet type on the BELF and profitability? According to this question, it is necessary to monitor the actual load factor and the change of the BELF over the years considering the fleet standardization index.

In the study by Atay et. al. (2022), it is stated that FSC airlines with a low fleet standardization index suffered major losses during the crisis COVID-19 but are in a more economically stable position than LCC airlines. Drawing these conclusions from the study, it is possible to say that FSC airlines have a more stable position in terms of their financial structure and support from non-operating passive income statements, in contrast to BELF escalations over the years.

At this point, we need to look at LF and the change in the carriers' BELF over the years. While the change in LF does not tell the whole story about fleet and financial profitability, it does allow us to derive some basic ideas about the distinction between homogeneous and heterogeneous fleet structures. Airlines with homogeneous fleet structures tend to have more LF than heterogeneous fleet structures. On the other hand, the fleet standardization index is another indicator of airline fleet costs and operational issues, but in this study, our main input data is shown in Fig. 3 below.

It is logical to say that the LF should be greater than the BELF for an airline to be profitable or in other words healthy. BELF values are always lower than LF values for all airlines in the U.S. Therefore, it is impossible to say anything about fleets and individual airlines based on Fig. 3. For this reason, each LF and BELF value must be analyzed individually.

Table 2
Non-financial performance indicators on airline companies.

Operational Indicators
Revenue per kilometer (RPK)
Occupancy Rate (LF)
Available Seat Kilometers (ASK)
Cost per Available Seat Kilometers (CASK)
Break Even Load Factor (BELF)

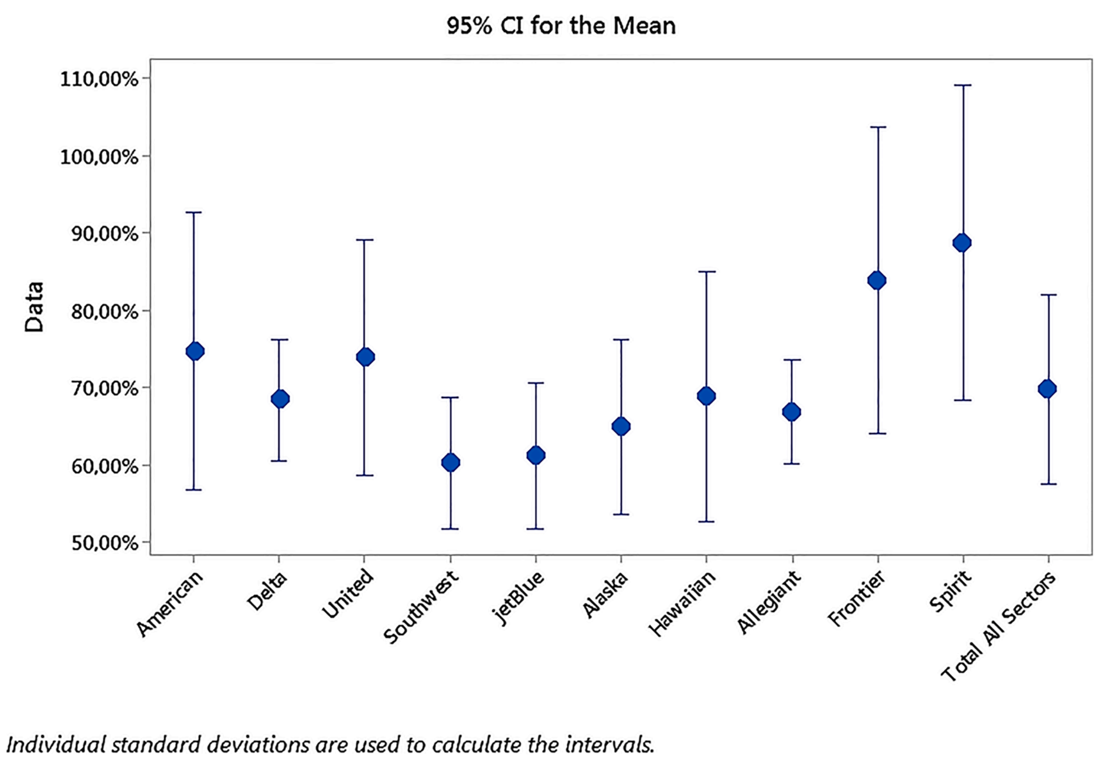

Fig. 2. Interval plot of airline companies break even load factor.

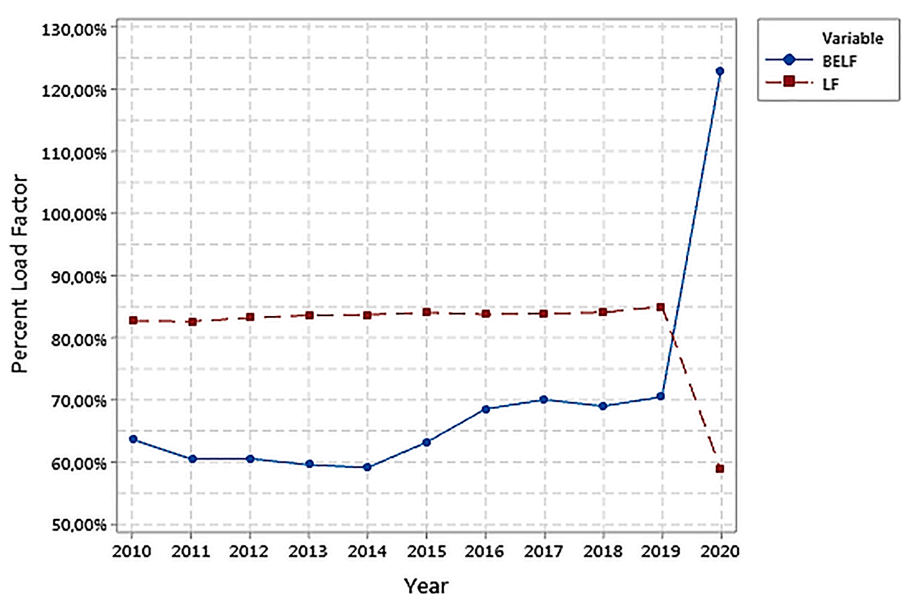

Fig. 3. Relationship between load factor (LF) and break-even load factor (BELF) in the U.S. Airline Sector.

However, since many data and airlines exist, these analyses need to be made simpler and easier to understand. With this in mind, the following equation was derived during the research process and referred to as the Load Factor Profitability Rate (LFPR), which is expressed in Eq. (2) below.

$$LFPR = \frac{Load\ Factor\ (LF)}{Break\ Even\ Load\ Factor\ (BELF)} \tag{2}$$

LFPR expresses airline load factor profitability per break-even load factor value. BELF value is expected to be lower than LF value for a profitable and healthy airline. When BELF and LF values converge, the risk of bankruptcy is expected to increase sharply (Goodfriend, 2003). Of course, it is not possible to say that the airlines whose LF is lower than the BELF will be bankrupt soon, but it reflects the large risk overall. This relationship is illustrated in Fig. 4 below.

Fig. 4 shows the profitability ratios of various airlines on an annual basis. A look at the figure shows that the COVID-19 process had a major impact in 2020. All airlines suffered a large loss compared to other years. However, it is important to note that the airlines that mostly belong to the LCC category have higher profitability compared to the others. This is an example of how fleet standardization and low-cost structure, along with ancillary revenues and the use of additional resources significantly change profitability. In the study conducted by Atay et al. the fleet standardization index was examined and compared with the profitability ratios. Fig. 5 shows the fleet standardization index of airlines.

The fleet considered for the calculated index is the fleet data announced at the end of 2019. The results of the calculated index are shown in Fig. 5. According to this, the airlines with the highest fleet standardization are Allegiant and Southwest, while the airlines with the lowest fleet standardization index are United and Delta. A striking finding here is that the fleet standardization of airlines operating with the LCC trend is higher, parallel to Barros and Peypoch (2009). The reason could be that FSC Airlines continues its operations according to the principle of differentiation and tries to offer a more flexible structure in terms of operations (Rozenberg et al., 2014). In addition, the principle of quality service (Business Class, First Class) has led to the diversification of the aircraft fleet to have an edge and respond to possible demand in the most appropriate way. This statement is confirmed by the work of West and Bradley (2008).

By saving costs and time in fleet management, it also has a positive impact on aircraft and pilot performance. If we consider that most companies operate similar types of aircraft, it is obvious that pilot performance has an impact on profitability. Considering the technological developments, it is foreseeable that the usual business process in logistics will change significantly, the need for personnel will decrease and productivity will increase by saving labor at minimal cost, especially in LCC airlines. In this direction, the need for overtime will be reduced, and this will have a cost-reducing effect. The fact that operations are performed to a certain standard and are lean affects the error rate and costs.

3.2. Response surface methodology

The Response Surface Methodology (RSM) has been widely used by scientists and engineers to determine the best parameter settings to improve processes and equipment since it was proposed by Box and Wilson in 1951. The Design of Experiments (DoE) approach is used by RSM to collect data and identify important interactions and factors that affect process response. The RSM is then used to develop a mathematical model to represent the causal relationships between causes and responses. Finally, to obtain optimal factor settings, the RSM optimizes the causality model as an objective function.

Therefore, it is difficult to perform planned experiments for continuous processes. Changing parameters during an ongoing process can disrupt production, increase the number of defective products, and drive up costs (Sukthomya & Tannock, 2005). Using observational data as input to RSM is one of the other solutions when direct testing is not practical (Chien et al., 2014; Sadati et, al.,2018). In some high-tech companies, smart data acquisition systems are often used to enable them to track changes in process or plant parameters in real-time. These data recorded in real-time are used as input to a mathematical model to make predictions, such as a system to predict maintenance schedules or product quality (Cerquitelli et al., 2021). Several studies (Fazeli Burestan et al., 2020; Hussain et al., 2021) on chemical engineering and food production have shown that the RSM-based observational data

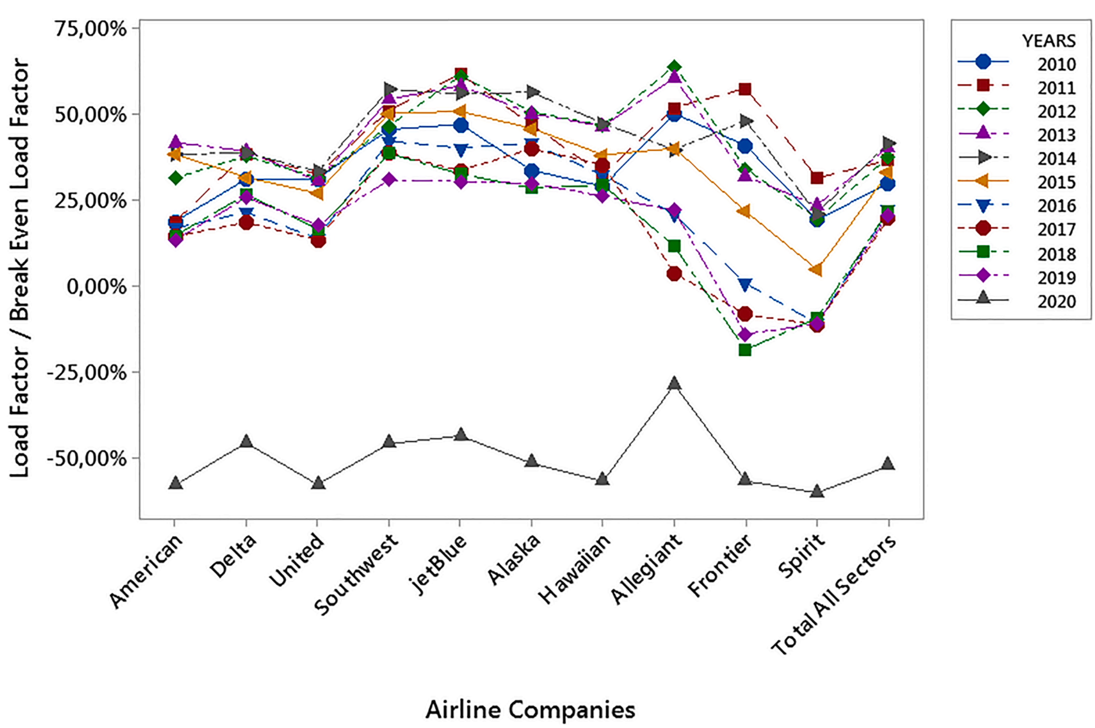

Fig. 4. Load factor profitability rate of airline companies in the U.S.

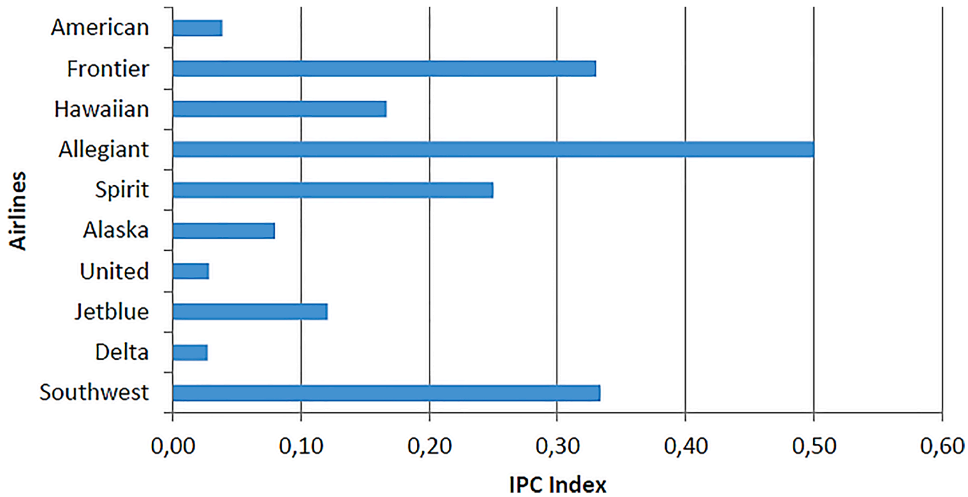

Fig. 5. Fleet standardization index of selected airlines (Atay et al., 2022).

(RSM-OD) provides a suitable mathematical model to determine the ideal factor configuration. As shown in the work of (Garg & Singh, 2017) for steel production and (Mahmoodi et al., 2019) with pollution removal, other studies used observed data from a running process or plant as input to RSM-OD.

However, a researcher's ability to manipulate his or her factor levels, as the DoE ideally allows, is considered by observational data and their similarities, including real-time record data, and already completed experimental data. Observational data are assumed to include circumstances that are serially correlated, extensive, and variable (Demchenko et al., 2014). Therefore, various adjustments are required in the selection of observations before using the data in RSM analysis, including the adaptive RSM model and optimization approaches, while still considering the ideal RSM concept. It should also be noted that the current growth of Big Data has accelerated the use of observational data. As an illustration of genuine manufacturing-oriented Big Data, Kong et al. have shown how recorded datasets can be used for process optimization and improvement (Kong et al., 2020). Massive datasets are produced by data recording technology, which also records operations and large datasets (Harding et al., 2006; Kuo & Kusiak, 2019; Tao et al., 2018).

3.2.1. *Overview of RSM for response optimization*

The classical RSM and its application in many research areas are discussed theoretically in this section. A thorough analysis of traditional RSM has shown that this approach has made important recent contributions. A strong theoretically based analysis and interpretation results from a developed, experimental RSM with fulfilled statistical assumptions. Yet, as several works in the literature have shown that observational data can be successfully incorporated into RSM, the idea of integrating them should not be discounted (Sadati et al., 2018).

3.2.2. *Classic RSM*

As indicated earlier, traditional RSM integrates three techniques into a sequential analysis (Fig. 6). The DoE is implemented in the first stage with the traditional RSM. In this step, the DoE participates in the preparation of the experiment, data collection, analysis, and

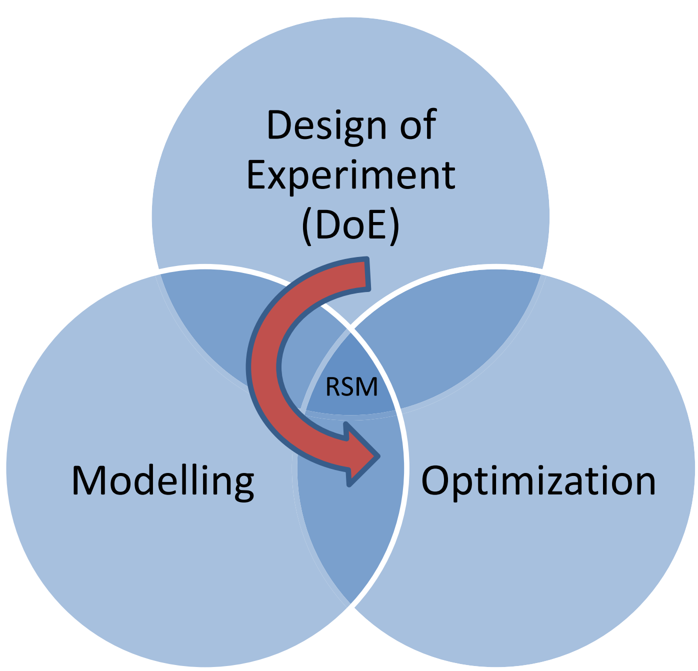

Fig. 6. Response surface methodology sequential analysis.

interpretation, and ensures that the experiment achieves its goals. The given process parameters can be evaluated separately from other parameters thanks to the orthogonality compliance of the DoE matrixes. To fit the data provided by the DoE, the conventional RSM uses a specific mathematical model as a second. The connection between the components or parameters as inputs and the responses as outputs is captured by this model. Due to its ease of interpretation and formal statistical derivation of all necessary assumptions during the modeling step, conventional RSM usually prefers a linear model. The third step, optimization, involves finding the factor (or parameter) that optimizes the response. In classical RSM, standard optimization techniques are preferred in conjunction with some theoretical methods such as mathematical optimization and desirability functions (Akteke-Ozturk et al., 2018). This methodology has replaced any modification as the best option since it satisfies the requirements of RSM for each stage. Determining the factors to be used in the analysis is another crucial preliminary stage of RSM. Researchers should arbitrarily select the factors in the RSM as the DoE is implemented. Considering the researcher's scope and area of expertise, they must identify the variables that have more subtle or significant effects on the response based on previous studies.

The response surface methodology is an extremely effective tool for solving various industrial problems. The problems in question can generally be examined in three categories (Myers & Montgomery, 2002):

- *Mapping a Response Surface on a Special Region of Interest:* A process that normally operates at certain levels may change levels in certain imperative situations. In this case, by appropriately estimating the unknown true response function for the region of interest, the engineer or researcher can reset the levels of the input variables by estimating the effects of said level change on the response.
- *Optimization of Response:* In the industrial world, determining the optimization conditions of a process is an important problem. Depending on the purpose set, it may be necessary to determine the levels of input that minimize or maximize the response.
- *Selecting Conditions to Meet Specifications or Customer Requirements:* In many response surface problems, there is more than one response that must be considered simultaneously. In such cases, it may be desirable to find conditions under which all the requirements of the process are satisfied simultaneously.

The relationship between a response variable and the input variables can be represented graphically as in Fig. 7. If you look at the figure, you can see the values of the response variable y corresponding to each value of the input variables ξ_1 and ξ_2. From this graphical perspective, the concept of Response Surface Methodology emerged.

In addition to this representation, the literature also uses a form of

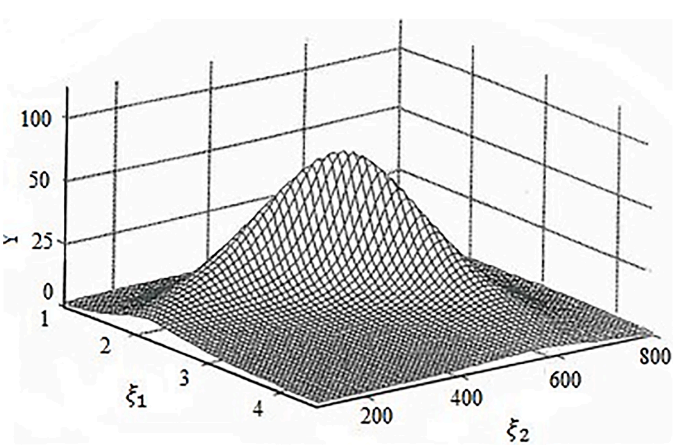

Fig. 7. A theoretical response surface.

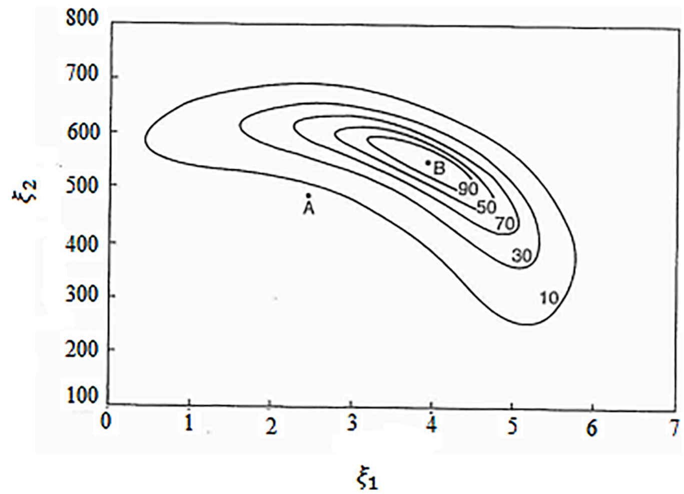

Fig. 8. Contour graph of a response surface.

representation called a contour plot, which consists of contour lines in the two-dimensional space shown in Fig. 8.

If the response of a product, process, or system y depends on the controllable input variables ξ_1, ξ_2,.., ξ_k the relationship between them;

$$y = f(\xi_1, \xi_2, \ldots\ldots\ldots, \xi_k)\varepsilon \tag{3}$$

is expressed as. In the equation in question, the unknown real response function can be complex and ε represents other sources of variability in that function. The statistical error term ε, which includes the measurement error of the response and other sources of error inherent in the process or system, is assumed to have a normal distribution with zero mean and σ 2 variance. In this case, the expression

$$E(y)\eta \ = E[f(\xi_1, \xi_2, \ldots\ldots\ldots, \xi_k)] + E(\varepsilon) \tag{4}$$

$= f(\xi_1, \xi_2, \ldots, \ldots, \ldots, \xi_k)$ is valid.

In response surface methodology, when the natural variables in equation (3) are transformed into coded variables such as x_1, x_2,…., xk equation (4) response function;

$$h \ = \ f(x_1, x_2, \ldots, x_k) \tag{5}$$

Turns into shape. Since the form of the response function is unknown in the response surface methodology, an approach needs to be developed for the relationship between response and input variables. This approximation usually refers to a low-order polynomial approximation in a relevant small region of the input variable space. If the response can be modeled well with the aid of a linear function of the input variables, then that approximation function

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \tag{6}$$

It is a first-order model. In case of curvature in the system,

$$\eta = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{i=1}^{k} \sum_{j=2}^{k} \beta_{ij} x_i x_j \tag{7}$$

a higher order polynomial such as a quadratic model given in Eq. (8) should be used. A general approximation polynomial for a response function f is based on a Taylor series expansion around the point $x10$, $x20$, xk 0 For example, a first-order model

$$f \cong f(x_{10}, x_{20}, \ldots, x_{k0} + \frac{\partial f}{\partial x_1} \lfloor x = x_0 (x_1 - x_{10}) + \frac{\partial f}{\partial x_2} \Big\lfloor x = x_0 (x_2 - x_{20}) + \ldots + \frac{\partial f}{\partial x_k} \Big\lfloor x = x_0 (x_k - x_{k0}) \tag{8}$$

It is developed from a first-order Taylor series expansion where x represents the vector of independent variables given in equation (6).

Many applications of response surface methods are sequential. First, the factors or variables that may be important in response surface studies must be identified. This is usually done by examining these factors and designing an experiment to eliminate unimportant ones. These experiments, called screening experiments, shorten the long list of factors thought to be important in explaining the response and ensure that the experiments to be conducted in the next phases are more effective with fewer tests and experiments. This phase of the experiments in question is referred to as the "zero stage" of the response surface studies (Myers et al., 2009).

After determining the important factors, the "first stage" of the response surface studies is initiated. At this stage, the experimenter aims to decide whether the current levels of the independent variables are near the optimal value of the response or whether the process is in a region far from the optimum. If the current levels of the independent variables are far from optimal performance, the researcher should adjust the process variables to optimize the process. In this stage, a first-order model and the optimization technique called the steepest increase method are used.

4. Numerical results

In this context, the data set was compiled to examine airline fleet structures and financial arrangements. The data obtained from the MIT Airline Data Project database was processed and used with the response surface methodology toolbox using the Minitab 19 package program. The main purpose of this method is that it has never been used in this field before and plays a good role in measuring reactivity and understanding relationships. Although there is no clear information in the literature about the minimum sample size required, the study created sufficient data sets and investigated the method.

4.1. Findings on load factor profitability rate

The main purpose of using the data in Table 3 above is to understand the relationship between airline operating statistics and fleet types. In this regard, using the RSM method, Departure per Aircraft Day and Average Seat Capacity were used as constant and independent variables, while Operating Revenue, Average Stage Length, and Average Daily Airborne Hours were used as dependent variables and their relationships were examined. The fleet standardization index and load factor profitability rate were also considered when examining these relationships.

Comparing the fiscal year 2020 load factor profitability values and IPC fleet standardization indexes from Fig. 9, it can be said that LCC-status airlines have lesser financial losses in the COVID-19 period data, but this cannot be stated definitively. This is because the loyalty programs and other capital assets used by the companies cannot be traced to how much space they take and amortize the loss. To better understand the situation, it is necessary to consider the route length flown.

A looking at Fig. 10 shows the lengths of the stage through which companies in the sector pass. From this figure, it can be said that the fleet standardization index decreases as the length of the stage increases. Although all this information can provide enough ideas to conclude, it is not enough to clearly explain some relationships and their effects. Therefore, a study was conducted to better understand the effects using the response surface methodology.

On the other hand, skimming Fig. 11, the LFPR and IPC values, as well as the percentage distribution of the full-time airline employees in the sector, give an idea of the dynamics of the sector. As can be seen, it is possible to see that the percentage distribution of full-time employees increases as the fleet standardization index decreases. In this case, as the number of employees increases, it can be said that the stage length flown has gotten longer by considering Fig. 10.

4.2. Findings of response surface methodology

Response surface methodology is a method used for improving processes, as mentioned in the previous sections. The main purpose of using this method in this study is to investigate and gain ideas about the fleet structure and behavior of physical and financial constraints. Since there are differences from country to country and region to region, an attempt was made to draw generalizable conclusions using the data specific to each region and to increase the realism of the models by using the data obtained here as input in future studies. In applying this method, MINITAB 19 software with a student license was used and the resulting graphs were visualized using the same package program. In building the model, the independent variables (factors) and responses were selected as shown in the following Table 4.

Factors and responses were analyzed by entering them sequentially into the software. Before the analysis, the regression coefficients were checked and found acceptable according to the significance level $p < 0.05$. To better understand the analyzed data, it was interpreted by examining the data of companies with high and low fleet standardization index separately.

The contour plot in Fig. 12 shows the response of the factors mentioned above to total revenue. The most important detail in this chart, which shows companies with a low IPC index on the right and companies with a high IPC index on the left, is the contrast between average seat capacity and daily takeoffs and landings. It shows that companies with a high IPC index should perform many takeoffs and landings during the day with a low seat capacity to achieve high annual profit rates, while companies with a low IPC index should perform few takeoffs with a high seat capacity. This situation essentially describes the characteristics of companies that operate direct domestic or international flights. This is because all short-term flights in the world are

Table 3
Dataset representation used for response surface methodology.

	Average Daily Airborne Hours		Average Seat Capacity		Average Stage Length		Departure per Aircraft Day		Total Operating Revenue (Bn)	
	2019	**2020**	**2019**	**2020**	**2019**	**2020**	**2019**	**2020**	**2019**	**2020**
American	9,46	6,53	185,56	170,69	1202,33	1131,91	3,61	2,61	45,76	17,34
Delta	8,91	4,94	189,58	181,63	1151,86	1077,95	3,56	2,08	47,13	17,12
United	10,81	4,85	198,76	178,87	1596,97	1593,95	2,84	1,29	43,26	15,36
Sub-Network	**9,68**	**5,37**	**191,04**	**177,49**	**1306,01**	**1273,20**	**3,35**	**1,96**	**136,15**	**49,81**
Southwest	8,85	6,03	153,63	155,03	748,46	743,73	5,10	3,49	22,43	9,05
JetBlue	10,17	4,68	152,01	158,61	1137,12	1219,67	3,99	1,75	8,09	2,96
Alaska	9,42	7,40	162,30	164,49	1299,41	1271,94	3,30	2,65	8,77	3,56
Hawaiian	8,76	3,44	239,44	214,53	961,15	870,06	4,24	1,83	2,83	0,84
Sub-Hybrid	**8,82**	**5,60**	**158,76**	**160,10**	**892,83**	**880,80**	**4,51**	**2,91**	**42,13**	**16,41**
Allegiant	6,82	4,82	171,34	173,22	871,30	875,42	3,40	2,40	1,75	0,93
Frontier	9,72	6,70	193,09	191,51	1050,40	998,14	4,11	2,97	2,51	1,25
Spirit	10,45	5,94	184,00	188,18	1008,86	1036,00	4,58	2,56	3,83	1,81
sub-ULCC	**9,24**	**5,80**	**183,22**	**184,63**	**983,46**	**979,75**	**4,12**	**2,62**	**8,08**	**3,99**

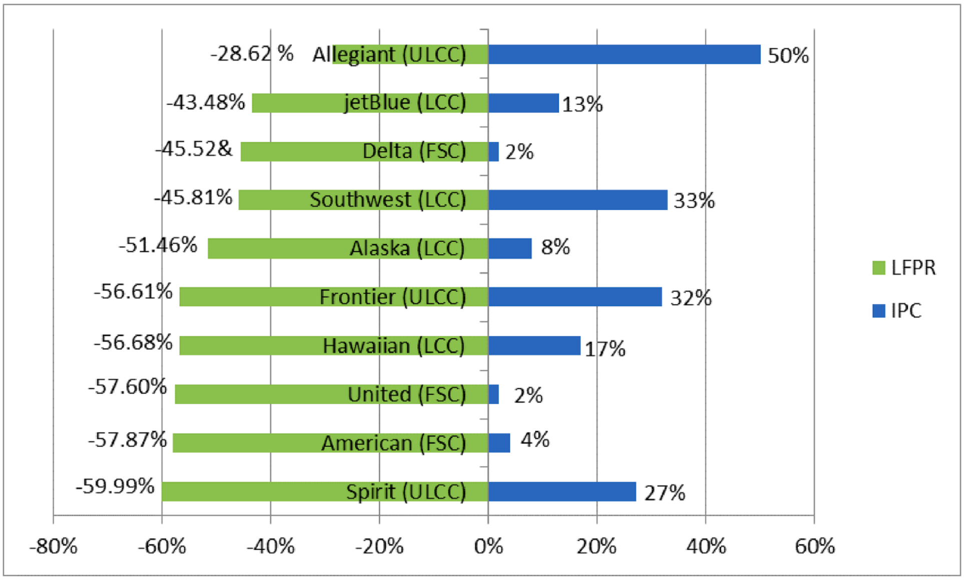

Fig. 9. IPC and LFPR relationship of airline companies in the 2020 fiscal year.

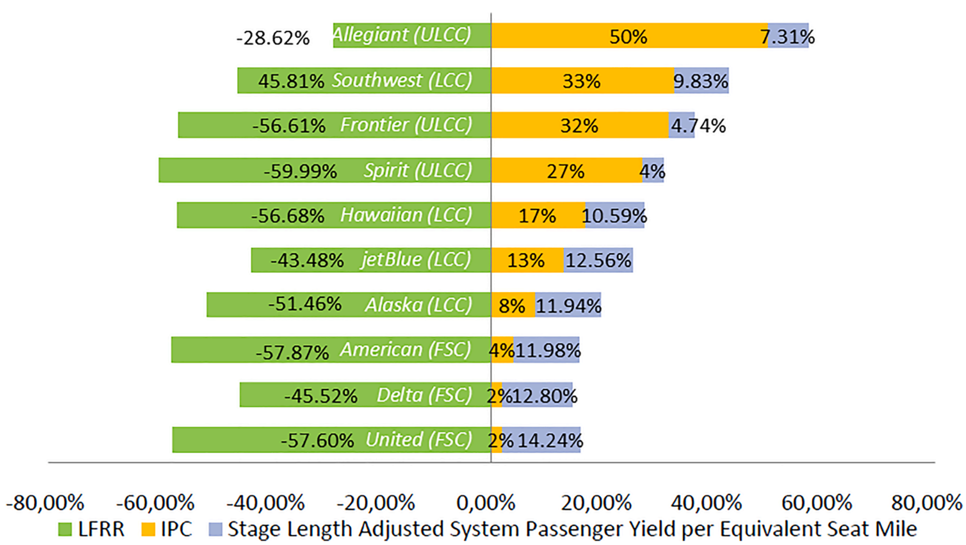

Fig. 10. IPC, LFPR, and Yield relationship of airline companies in the 2020 fiscal year.

operated by LCC or ULCC class companies, and their IPC indices are high. On the other hand, network airlines continue their activities with longer intercontinental flights.

Fig. 13, on the other hand, shows the contour graph, which represents the responsiveness of the average stage length. Similar to other graphs, the responsiveness of companies with a high IPC index is shown on the left and a low IPC index on the right. Fig. 12 confirms that the average number of seats and daily takeoffs and landings should be increased to extend the stage length of companies with a high IPC index. Similarly, for companies with low IPC index, to be profitable and active, the average seat capacity should be increased, while the daily takeoff and landing amount should be reduced, and they should fly on a longer route. In this case, it can be seen that the data is mutually supportive of the normal flow of life, while the other issue that needs to be examined is the length of stay in the air. This is because the length of time an aircraft is in the air is directly related to the number of landings and takeoffs the aircraft makes each day and the average stage length. If the final response measurement can provide an answer that supports the first two, we are assured of having data that can be used as input.

Although this information is not newly acquired or discovered, it is important to see the changes in the behavior of the various airlines over time. This is because periodic studies of these processes can determine whether it is possible to use different airline networks with new or hybrid business models and determine the policies that should be applied to ensure the continuity of the airline network.

Fig. 14 shows the differences in flight time according to the fleet standardization index. According to these contour plots, flight time in fleets with a high fleet standardization index is directly related to the number of aircraft takeoffs and landings. In other words: If the aircraft flies fast on short routes and the number of takeoffs increases, the time in the air also increases. On the other hand, when fleet standardization is low the length of time in the air can be seen even though the daily number of takeoffs and landings is low. This can be explained by the fact that fleet types with low fleet standardization operate with longer stage lengths. Another finding is that seating capacity is high for fleets with low standardization and low for fleets with high standardization. In this case, companies with low fleet standardization are more profitable on long routes, while fleets with high fleet standardization are profitable on

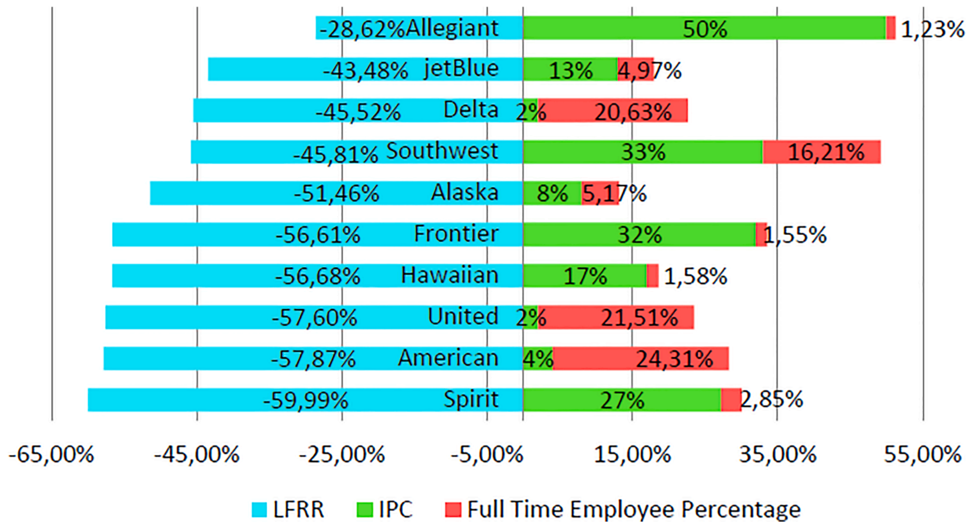

Fig. 11. IPC, LFPR, and Full-time employee relationship of airline companies in the 2020 fiscal year.

Table 4
Response surface methodology factor and response classification.

Factors	Departure per Aircraft Day
	Average Seat Capacity
	Total Operating Revenue (Bn)
Responses	Average Stage Length
	Average Daily Airborne Hours

short routes.

However, this requires the delineation of airlines that have adopted the ULCC, LCC, and FSC concepts with the fleet standardization index. In other words: If the stage length exceeds the limit, the question of the need to increase the fuselage of the aircraft in the fleet must be answered. In this context, the classification of aircraft by fuselage types over the years is shown in Fig. 15, with data compiled from the USA, one of the countries with the largest aircraft fleet. All the required data were obtained from the corresponding website of the project called Airline Data Project, compiled and provided free of charge by MIT, and the corresponding airlines were verified through the SEC. The data provide only the number of aircraft operated by all airlines in the USA, broken down, by fuselage type. The numbers are given without distinction by make or model.

As can be seen in Fig. 15, the number of narrow-body jets in airline fleets has gradually decreased over the years, while the number of large narrow-body jets has continued to increase. This is because the increase in seating capacity of narrow-body jets and the ability to accommodate more passengers without changing their wingspan have made them aircraft that can take off and land at any airport in the world. This situation has increased the importance and popularity of these fleets over time. In addition, large narrow-body aircraft offer great advantages not only in carrying passengers but also in carrying cargo in the cabin among passengers. On the other hand, the fact that the fuel consumption and greenhouse gas emission values have been brought to a better point by the innovations in engine technology can be considered as the main reason for the widespread use and preference of these new generation aircraft.

For example, the Airbus A320neofamily (neofor new engine option) is an evolution of the A320 family of narrow-body aircraft manufactured by Airbus. The A320neofamily is based on the previous A319, A320, and A321, renamed A320ceo for 'current engine option'. New engines have been added in the form of the CFM LEAP-1A or Pratt & Whitney PW1000

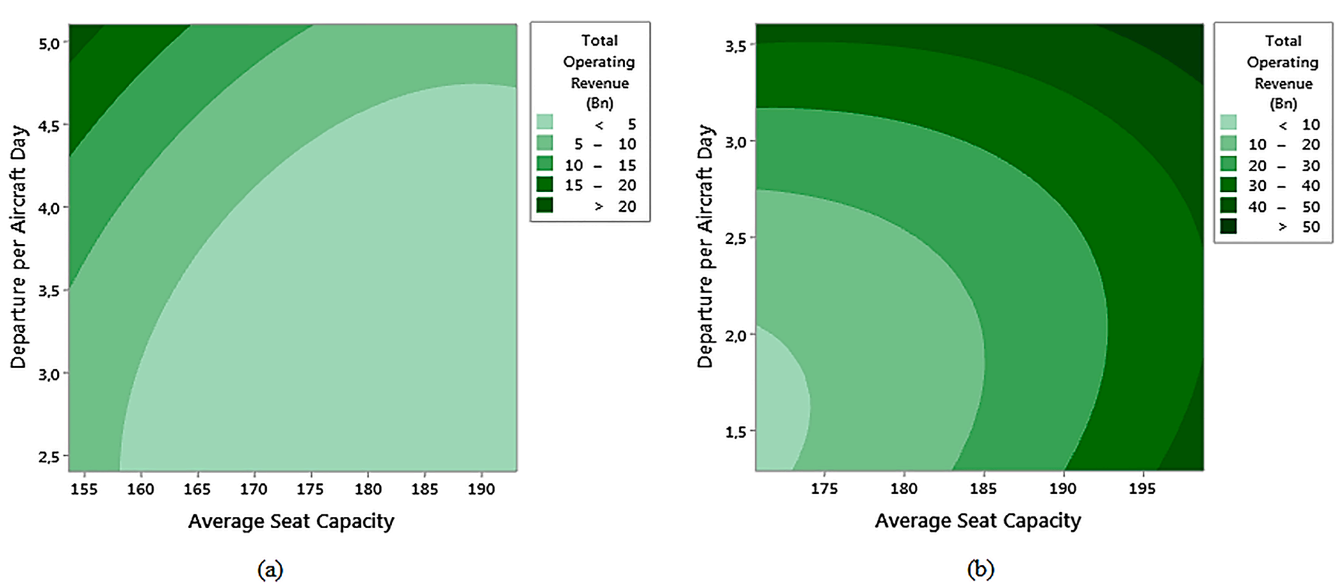

Fig. 12. Contour graph of total operating revenue for (a) high IPC and (b) low IPC.

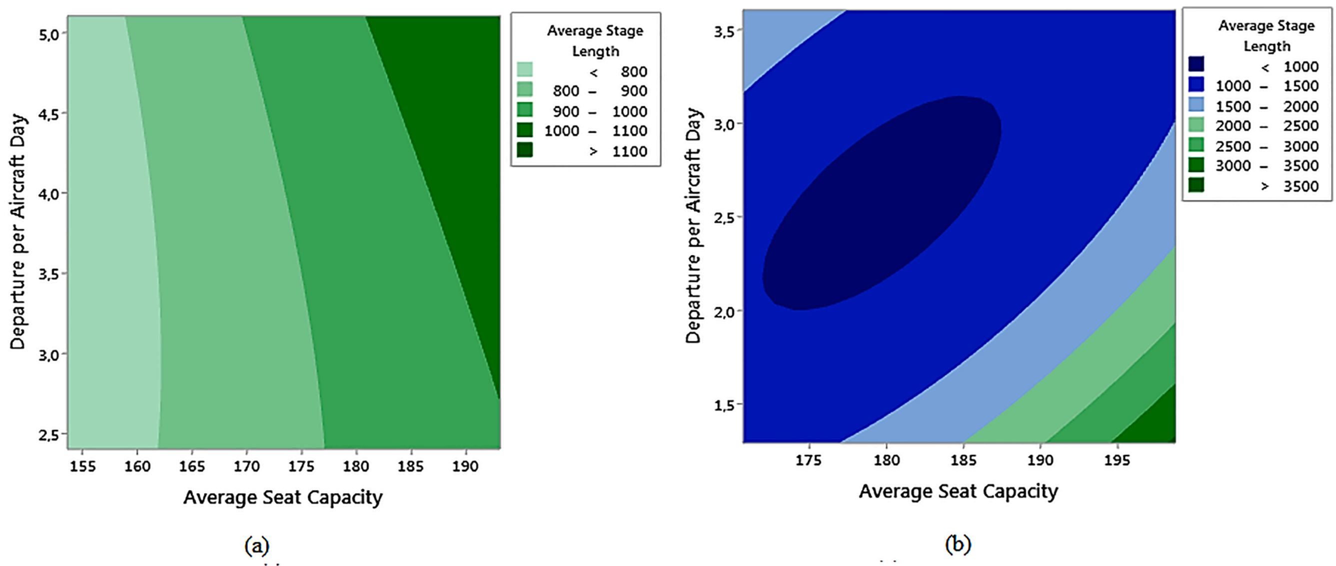

Fig. 13. Contour graph of average stage length for (a) high IPC and (b) low IPC.

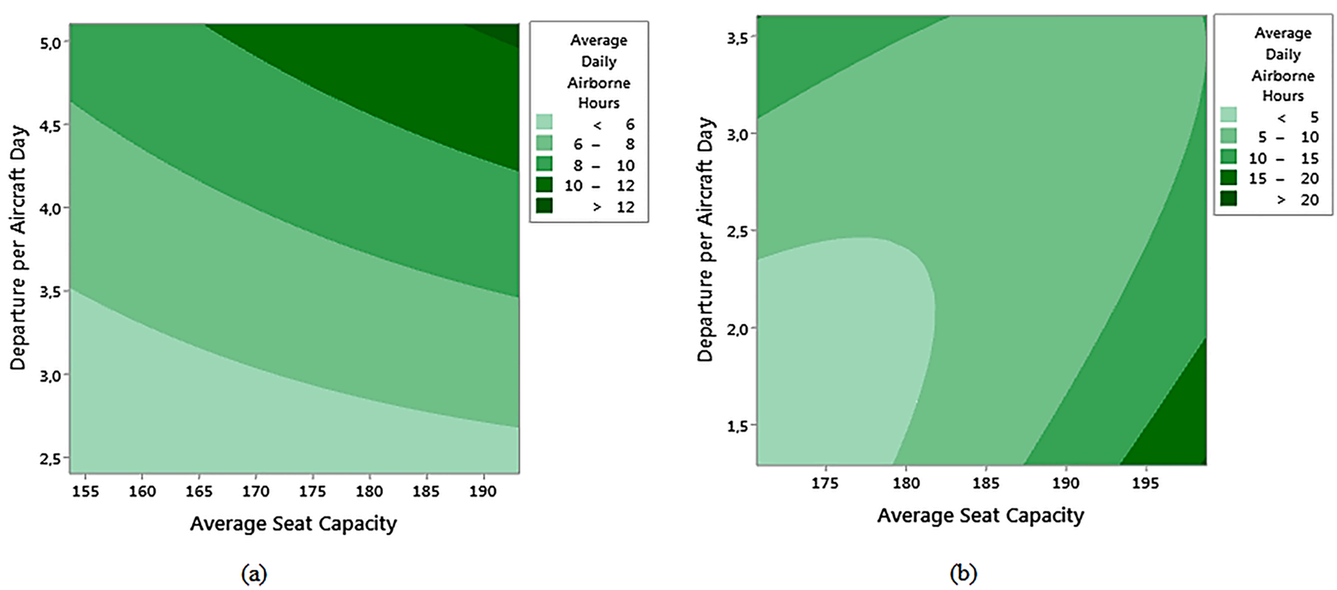

Fig. 14. Contour graph of average daily airborne hours for (a) high IPC and (b) low IPC.

G engines which, equipped with Sharklets as standard, are 15 to 20 % more fuel efficient than the A320ceo (Enhanced) family (Airbus, 2023).

Fig. 16 from the annual report published by IATA provides information on the development of aviation in Europe and conveys the trends in passenger and cargo transportation. From the transferred trend curve, it can be seen that the impact of the global COVID-19 pandemic in 2020 will be attempted to be eliminated in 2021 and the amount of revenue will be increased. From this point of view, it can be said that Turkey, which acts as an international and domestic hub, has also been hit hard by this recession. The fleet that is being built under these conditions should take this situation into account. So, while the length of the routes to be used and the limit of demand for these routes should be known, the income speed should also be considered.

5. Conclusion

Fleet analysis using the Response Surface Methodology examined the purposes served by the fleet structures of existing airlines and discussed the considerations that should be made in building a fleet. The main reason for all these discussions is to select the most realistic parameters for the mathematical model to be built and to ensure that the model can serve real life and maintain its dynamics. It can be said that air transport has brought many changes with the recent changes in the world. It is also true that the demand in the civil aviation industry is very high, especially with the increasing speed demand and fast transportation trends. On the other hand, the reasons affecting the whole world such as the pandemic and the disruption of air transport have affected the operation on a sectoral basis and the global economy, making the operation expensive (Sun et. al., 2023). It is known that under these conditions, although many airlines go bankrupt, new airlines are also established.

This situation can be seen as a step taken to meet the demand for cheaper air travel while increasing competition in the market. However, it should not be ignored that load factor and flight time have a direct impact on profitability when considering the route flown. From this point of view, even if we have received certain information about the behavior of the fleet, we must know that the fleets to be built will behave

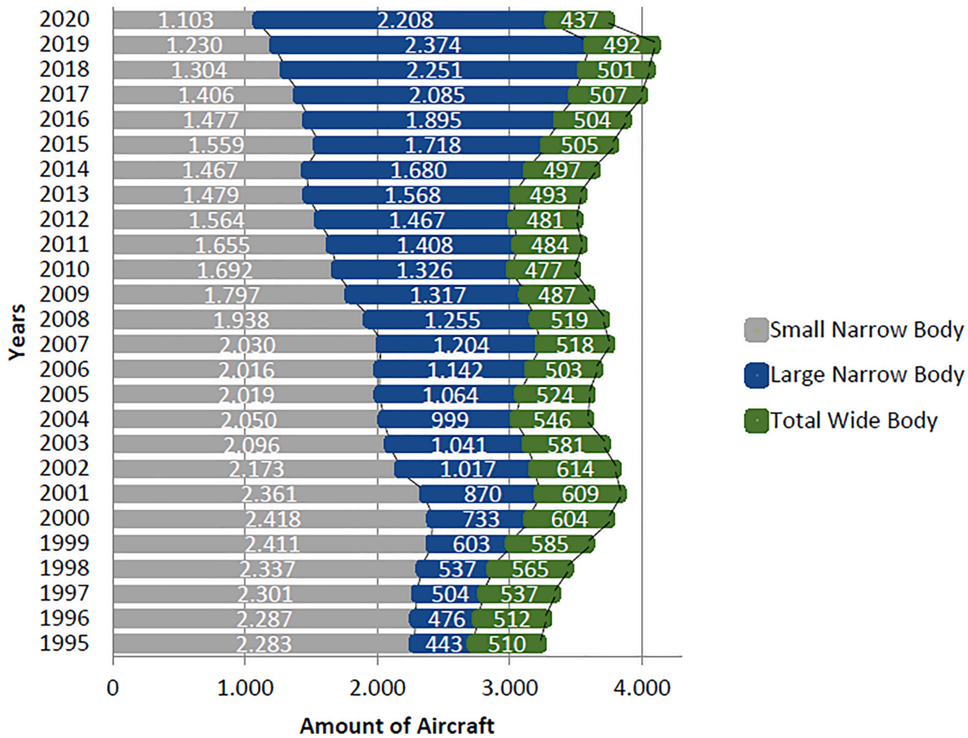

Fig. 15. Amounts of aircraft by fuselage type in the U.S. (MIT, 2023).

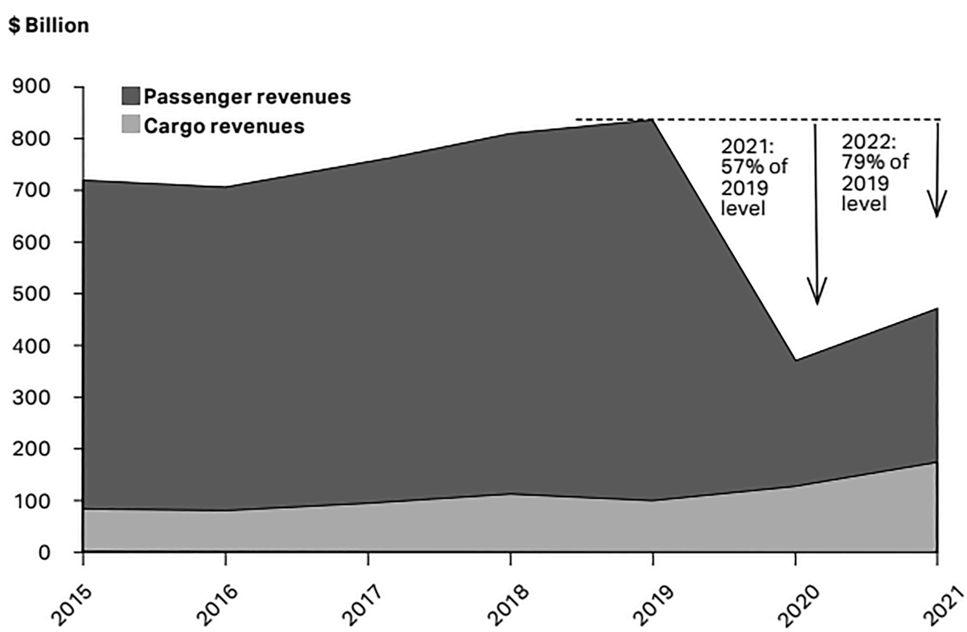

Fig. 16. Current airline revenues due to operation type (IATA, 2023).

Table 5
Response optimized values for each factor.

Type	Average Seat Capacity	Departure per Aircraft Day	Total Operating Revenue (Bn)	Average Stage Length (km)	Average Daily Airborne Hours	Composite Desirability
High IPC	153,629	3,8219	11,6999	732,551	6,5259	0,688,634
Low IPC	189,971	3,2782	40,4668	1071,8	8,0135	0,718,535

differently in different regions of the world and must act accordingly. A detailed representation of the numerical values of the graph can be found in Table 5.

According to Table 5, the highest efficiency that can be obtained from the operations that can be performed with the lowest flight effort under minimal conditions was studied, and the results were obtained for both high and low IPC indices. According to the results, it is assumed that airlines with a high fleet standardization index should fly with a minimum capacity of 153 seats, while fleets with a low fleet standardization index should fly with a minimum capacity of 189 seats. Furthermore, if we look at the Daily departure volume, we find that the fleets with high fleet standardization have a high value, while the fleets with low index must take off less. This situation is also consistent with the flight hours data of the aircraft because while the fleets with high standardization must stay in the air for at least 6.5 h, this value is at least 8 h for the fleets with low standardization. In the values for the average stage length, it can be seen that the fleets with high standardization should determine a minimum of 732 kms, while this value is a minimum of 1071 kms for the fleets with low standardization. When looking at the total operating income, it can be seen that the income in companies with low standardization is 4 times higher than in companies with high standardization.

This situation is not only related to operations and the fleet, but may also be due to the anchor income, loyalty programs, and additional investment income offered by the company. Since these values could not be included in the model, the composite desirability of the model took low values. It cannot be said that the reliability of the model is very high since political variables and additional sources of income cannot be included in the model, but the model can be informative and guiding.

6. Discussion

The results of this study provide actionable strategies for fleet sustainability, focusing on efficiency and adaptability in fleet management. By utilizing Response Surface Methodology (RSM) to optimize fleet parameters and examining critical factors like fleet standardization, seat capacity, and flight time, the analysis offers airlines a practical approach to sustainable operations amidst fluctuating global conditions (Wandelt et. al, 2024). The findings underscore the value of strategically planning fleet structures with attention to factors such as seat capacity and average stage length. For instance, airlines with high fleet standardization indices may focus on shorter, more frequent routes with medium-sized aircraft (minimum 153 seats), while those with low standardization indices may maximize profit on longer routes with higher seating capacity (minimum 189 seats). This segmentation enables airlines to align route planning and fleet utilization with demand patterns, maximizing revenue while minimizing unnecessary fuel expenditure and a critical element in sustainable fleet management.

The Break-Even Load Factor (BELF) and analysis of operating income reveal how airlines can achieve financial stability without compromising efficiency. High-standardization fleets benefit from increased daily departures, indicating that fleet homogeneity can support a sustainable operational rhythm by minimizing maintenance variability and enhancing route flexibility. Conversely, airlines with low-standardization fleets might benefit from reduced frequency and longer stage lengths, focusing on high-revenue flights that justify higher operating costs. These insights help airlines avoid overextension while maintaining profitability, a key sustainability strategy in uncertain economic climates. The model's composite desirability scores, though modest, offer a clear framework for understanding the trade-offs between operational efficiency and revenue generation. By identifying minimum thresholds for airborne hours and seat capacity, airlines can make informed choices about fleet configuration and schedule adjustments. While factors like loyalty programs or external income were not included in the model, the desirability scores guide airlines in aligning fleet operations with profitability goals, providing a foundation for incorporating additional income streams in future planning.

This study's findings emphasize the need for adaptability, as fleets may need to respond dynamically to shifting market demands, regulatory changes, and external disruptions. The optimized fleet configurations and operating strategies identified here encourage flexibility, helping airlines maintain operational sustainability across diverse regions. By tailoring fleet composition and deployment to local demand and cost structures, airlines can manage global uncertainties with a resilient, scalable approach (Sun et. al., 2022). The integration of RSM findings into fleet management strategy enables airlines to operate within fuel-efficient configurations and maintain optimal load factors. This approach directly addresses emission reduction, a critical element of sustainable aviation. The study's findings can guide airlines in selecting routes, fleet types, and operational practices that align with environmental goals and regulatory pressures to cut carbon emissions.

CRediT authorship contribution statement

Metehan Atay: Writing – original draft, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Serap Ulusam Seckiner:** Writing – review & editing, Supervision. **Yunus Eroglu:** Writing – original draft, Visualization, Supervision.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript

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