An Airline Profit Management Model with Overbooking and No-Shows

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Abstract: This research presents a model for airline profit optimization considering information such as demand forecasts, seat inventory, operational costs, overbooking penalties, expected no-shows, and time-dependent fare classes. The main decisions in the model are the selection of the aircraft, the number of seats sold per fare, including overbooking, and the number of denied seats. The model incorporates probabilistic information, like the expected demand and the expected proportion of no-shows. The model is constructed as a deterministic mixed-integer program. Some data was estimated using information acquired from different industry sources, and some data was set with reasonable estimations. A factorial experiment was designed to understand the importance of different parameters. The input variables were the overbooking compensation penalty, the no-show probabilities per fare and time block, and the seat demand. Using a statistical analysis, it was determined that the no-show estimation has the most significant impact on the total revenue, and the demand forecast after that. These results highlight the importance of precise estimations to increase the airline's profit.

1 INTRODUCTION

The airline industry is a vital engine for the global economy, facilitating international trade, tourism, and cultural exchange. By connecting countries and fostering stronger diplomatic and economic ties, the industry plays a pivotal role in enabling both the movement of people and goods across borders. Airlines act as critical links in the global supply chain, ensuring the smooth transport of essential goods and services. This role becomes especially important in an increasingly interconnected world, where efficient air transportation can bolster trade partnerships and enhance supply chain resilience.

Managing flight operations in such a complex, globalized industry requires airlines to consider a wide range of factors. Key variables like flight schedules, passenger capacity, routes, and market demand must be balanced to ensure efficient and profitable operations. The rapid evolution of the market has driven the adoption of modern technologies and sophisticated frameworks. This shift has allowed airlines to not only streamline their operations but also develop advanced pricing strategies to remain competitive in a crowded market.

One of the central techniques used to manage this complexity is profit management, which optimizes the relationship between supply and demand by adjusting ticket prices, seat availability, and operational expenses based on real-time market conditions. Some parameters that must be considered for the balance of ticket pricing and seat allocation are customer segmentation, seat capacity, and the handling of cancellations and no-shows. In anticipation of no-shows and last-minute cancellations, airlines often sell more tickets than the actual number of available seats. This approach, while beneficial in maximizing revenue, introduces a risk of penalties when too many passengers show up and there are insufficient seats. However, research

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shows that the revenue generated from overbooking usually outweighs the costs associated with compensating passengers who are denied boarding (Rothstein, 1985; Ely et al., 2017). This practice exemplifies the delicate balancing act airlines must perform between profitability and customer service.

The effective management of overbooking requires sophisticated modeling, especially when cancellations and no-shows are factored in. Airlines often use data-driven methods, relying on historical data and forecasting tools to predict demand and cancellations accurately. Studies such as those by (Subramanian et al., 1999) and (Minga et al., 2003) highlight various models that airlines employ to manage these uncertainties. By optimizing booking limits based on real-time and historical data, airlines can minimize losses while ensuring they meet customer demand. Algorithms and adaptive methods, like those developed by (Ball and Queyranne, 2009), have proven effective in refining demand estimates and setting optimal booking limits.

The application of linear programming has been a common thread across numerous studies in the airline sector, emphasizing its importance in optimizing both passenger and cargo operations. (Belobaba, 1987) explored fare segmentation, showing how airlines adjust ticket pricing based on advance bookings. This segmentation allows airlines to offer lower fares to early bookers while limiting the number of tickets in each fare class to prevent financial losses. (Belobaba et al., 2009) also noted that over 30% of denied boarding requests result from passengers seeking alternatives after being denied a seat, reflecting the complexity of managing demand and ticket sales.

(Kunnumkal et al., 2012) delved into overbooking, a widespread practice where airlines sell more tickets than available seats, accounting for potential no-shows. They employed randomized linear programming to model overbooking scenarios and no-shows, providing a strategy that helps airlines maximize profits while minimizing the risk of unsold seats. Introducing an upper bound criterion in their research helps airlines determine the optimal overbooking levels, mitigating financial losses from customer no-shows.

(Aydin et al., 2013) study some dynamic programming models for airline revenue management considering overbooking and no-shows. (Soleymanifar, 2019) addresses four constraints relevant to airline revenue management problem: flight cancellation, customer no-shows, overbooking, and refunding. They develop a linear program closely related to the dynamic program formulation of the problem, which is later used to approximate the optimal decision rule for rejecting or accepting customers. Although Dynamic Programming is the preferred approach used in the literature, there are some linear programming formulations close to the one proposed in this work in (Gaul and Winkler, 2019), (Gaul and Winkler, 2019), and (Xiao et al., 2024).

In this research, we extend the model proposed by (Kunnumkal et al., 2012) and originally presented by (Bertsimas and Popescu, 2003) to incorporate some elements like the selection of the aircraft based on costs and capacities and an ethical control on the overbooking. We also present a sensitivity analysis with variations to a base instance to understand the significance of the parameters on the profit objective function. The main contributions of this paper are the inclusion of aircraft selection and ethical overbooking, along with the use of a design of experiments to study the significance of some parameters on the total profit.

The structure of the rest of the paper is described next. The Methodology in Section 2 explains the description of the problem, the mathematical model proposed, and the data used for the case study. Section 3 describes the results of the base instance and the results of the sensitivity analysis using a design of experiments. Section 4 shows the main conclusions of the study and the proposed future work.

2 METHODOLOGY

In this problem, we have different types of aircrafts, with different capacities and operational costs. The seats of the aircraft are divided by fare classes, and each class has a fare that changes as time passes. Time is "discretized" as time blocks, with the main idea being that once the seats for a time block are sold, the price increases when the time block is closer to the departure time. Some important parameters independent of the decision-making are the compensation fee for denied boarding, the expected demand of seats for fare class and time block, the probability of no-shows for seats sold per time block and fare class. Other parameters, dependent on the decision-making are the fares for class and time block, the maximum portion of sold seats that show for check-in and are denied boarding, and the minimum capacity to cover for an aircraft to be operated. The variables are the seats sold, the denied boarding seats, both per aircraft, fare class, and time block, and the variable that determines the operation of the aircraft. Following is shown the list of sets, parameters and variables.

Sets:

J Set of products (fare classes), $j = 1, ..., n$

T Set of time blocks, $t = 1, …, T$

I Set of aircrafts, $i = 1, …, |I|$

Parameters:

f_{ijt} price of fare class j in aircraft i in time block t

θ_{ij} penalty for denying boarding of fare class j in aircraft i

u_i fixed cost for operating flight in aircraft i

q_{jt} show probability for a seat (passenger) in fare class j sold in time block t

c_{ij} seat capacity for fare class j in aircraft i

p_{jt} expected demand for fare class j sold in time block t

α maximum proportion of sold (shown) seats with denied boarding

β minimum capacity utilization to operate one aircraft

Variables:

y_{ijt} seats in aircraft i for fare class j sold in time block t

w_{ijt} denied boardings (seats) in aircraft i for fare class j sold in time block t

v_i binary variable, equal to 1 if aircraft i is operated, equal to 0 otherwise

With these variables, a mixed-integer program is constructed to maximize the profit with the following objective function and constraints:

$$Max \sum_{i\in I, j\in J,\ t\in T} [f_{ijt}y_{ijt} - \theta_{ij}w_{ijt}] - \sum_{i\in I} u_i\, v_i \tag{1}$$

Subject to:

$$\sum_{t\in T} q_{jt}y_{ijt} - w_{ijt} \le c_{ij}v_i, \forall i \in I, j \in J \tag{2}$$

$$\sum_{i\in I} y_{ijt} \le p_{jt}, \forall j \in J, t \in T \tag{3}$$

$$w_{ijt} \le \alpha q_{jt}y_{ijt},\ \forall i \in I, j \in J, t \in T \tag{4}$$

$$\sum_{j\in J, t\in T} q_{jt}y_{ijt} - w_{ijt} \ge \left(\beta \sum_{j\in J} c_{ij}\right) v_i, \forall i \in I \tag{5}$$

$$y_{ijt}, w_{ijt} \in Z^{\ge 0},\ \forall i \in I, j \in J, t \in T \tag{6}$$

$$v_i \in \{0,1\},\ \ \forall i \in I \tag{7}$$

In this model, the objective function (1) determined that the profit is the sum of the sold seats minus the penalty for denied boarding, all minus the operational cost of selecting certain aircraft for the flight. Constraints (2) are the constraints for not exceeding the seat capacity per aircraft. Constraints (3) establish that the number of sold seats does not exceed the demand. Constraints (4) determine that the seats (passengers) that show for check-in whose boarding is denied do not exceed a certain proportion of the seats sold, controlled by parameter α. Constraints (5) help to ensure that a certain capacity of the aircraft is sold to operate the flight. Constraints (6) and (7) are the domains for the integer and binary variables.

The model considers both overbooking and no-shows, with constraints ensuring capacity limits are respected. The number of seats denied boarding should not exceed a certain percentage of total sales. The introduction of binary variables accounts for whether a flight will operate based on a threshold capacity to ensure flights only operate when economically viable. This constraint prevents revenue losses due to low-demand flights.

Even after accounting for no-shows, seat sales may exceed the available capacity on certain flights, forcing airlines to deny boarding to some passengers. This scenario suggests collaboration between airlines to accommodate denied passengers. If the compensation fee for denied boarding is too cheap, there is an incentive for a high overbooking. In this case, the “ethical selling” constraint in Equation (4) prevents an excess of boarding denials.

The model was programmed in AMPL, using Gurobi 10.0.1 as the optimizer, and solved in a laptop with Intel Core i7 CPU at 2.8GHz with 32 Gb RAM. An instance was constructed based on an example flight. A one-leg-based approach is adopted for simplicity, for the Frankfurt-Mexico City route. The flight can be done in 4 different aircraft with the capacities shown in Table 1.

Table 1: Aircraft capacities per fare class.

Aircraft	Economy	Economy Plus	Business
Boeing 747-8	244	32	80
Airbus A320	96	48	-
Embraer E-170	56	-	20
Embraer E-175	60	8	20

The fares for the flights for each aircraft and class are shown in Table 2.

Table 2: Fare per aircraft and class, in €.

Aircraft	Economy	Economy Plus	Business
Boeing 747-8	413	663	1288
Airbus A320	351	521	-
Embraer E-170	425	-	1159
Embraer E-175	339	389	1154

The sale of seats was divided into three time blocks. The fare per class increases 50% from the first to the second time block, and it increases 70% from the first to the third block. The third block is closer to the departure time scheduled for the flight. The base compensation fee for denying boarding is the ticket fare plus 600 €. The operational costs for the flight in the different aircraft are estimated from information of (EUROCONTROL, 2023), shown in Table 3.

Table 3: Operational costs, in €.

Aircraft	Operational cost
Boeing 747-8	189265
Airbus A320	105542
Embraer E-170	268065
Embraer E-175	105542

In the base instance, the demand was assumed the same as the available capacity per fare class. This demand was divided into a proportion of 30% for the first time block, 30% for the second time block, and 40% for the third time block. The parameters determined by the decision maker were set to $\alpha = 0.1$ for the maximum seats with denied boarding, and $\beta = 0.7$ for the minimum capacity threshold for using a certain aircraft.

The proportion of "shows", i.e., the passengers who bought a seat and who showed up to check-in at the airport or who did not cancel their purchase, is shown in Table 4. Since the fares are more expensive in the last time block, closer to the departure time, the proportion of no-shows is lower.

Table 4: Proportion of "shows" for check-in.

Fare class	Time block 1	Time block 2	Time block 3
Economy	0.6	0.6	0.75
Economy Plus	0.7	0.7	0.85
Business	0.8	0.8	0.95

3 RESULTS

For the base instance, the results are summarized in Table 5. Only the flight operated by the Boeing 747-8 was selected. Table 5 shows the number of seats planned to be sold for this aircraft per fare class and time block. The behavior of the passengers is to consume the cheapest seats first, thus depleting the seats planned for sale in the first time block. Once those seats are sold, the fare is changed to the next time block, with a more expensive price. After the seats of this block are sold, the fare changes again, being more expensive closer to the departure time.

Table 5: Seats sold per fare class and time block.

Fare class	Time block 1	Time block 2	Time block 3
Economy	42	137	182
Economy Plus	0	15	17
Business	7	36	48

Because of the proportion of no-shows, even if the number of sold seats exceeds the capacity of the aircraft, there is no need to deny boarding because of the overbooking. The expected profit was 268197 € for this flight. When the demand is high, and more than one aircraft is selected for a flight, a negotiation with the airport may allow different flights operated with different aircrafts with a short difference in the departure times.

A factorial experiment was designed to understand the impact of changes in some parameters. Three parameters were modified, the compensation fee for denying boarding to a sold seat, the no-show proportion per fare class and time block, and the expected demand. Table 6 shows the low and high levels for the compensation fee with respect to the base instance. These levels were explored because the base instance did not deny boarding to overbooked seats, and we wanted to know if the fee reduction may incentivize boarding denials. Table 7 shows the low and high levels for the "show" proportion. These levels were set to explore the effect of the variability in the no-shows. The high level is the combination of "high" for all the fare classes, and the same happens for the "low" level. Table 8 shows the low and high levels for the change of demand with respect to the base instance. These levels were set considering periods of high demand, like holidays and vacations.

Table 6: Low and high levels for the compensation fee.

Level	Change in the compensation fee
Low	25%Ticket price + 600EUR
High	50%Ticket price + 600EUR

Table 7: Low and high levels for the proportion of "shows" for check-in.

Fare class	Level	Time block 1	Time block 2	Time block 3
Economy	Low	0.55	0.55	0.70
	High	0.65	0.65	0.80
Economy Plus	Low	0.65	0.65	0.80
	High	0.75	0.75	0.90
Business	Low	0.75	0.75	0.90
	High	0.85	0.85	1.00

Table 8: Low and high levels for the demand.

Level	Change in the demand
Low	+40% in every period
High	+70% in every period

Thus, a full factorial of 2^3 experiments was run. Table 9 summarizes the averages of the instances with the high and low levels of the compensation fee. Table 10 summarizes the averages of the instances with the high and low levels of the "show" rate. Table 11 summarizes the averages of the instances with the high and low levels of demand. The output variables are:

- Total profit;
- %sale per fare class, i.e. the proportion of seats sold from the expected demand;
- %denied per fare class, i.e. the proportions of denying boarding seats from the total of sold seats;
- %average aircraft utilization, i.e. the proportion of seats used from the available capacity.;

The results for some instances indicated that more than one aircraft should be selected. It becomes evident that this is necessary for periods of high demand where additional capacity is needed. In this case, the averages reported consider the accumulated quantities for all the aircraft selected.

As can be observed, an increase in the compensation fee and the proportion of "shows" reduce the total profit. And a high demand increases the profit. In all the cases, the levels proposed generated some denied boarding seats. In all the cases, the aircraft utilization is above 99%.

Table 9: Averages of instances with high and low levels of the compensation fee.

Output variable	Low level	High level
Total profit	314841.96	308618.93
%sale Economy	76.22	72.26
%sale Economy Plus	80.88	77.03
%sale Business	54.44	54.44
%denied Economy	3.48	0.34
%denied Economy Plus	5.12	2.12
%denied Business	7.91	7.91
%average aircraft utilization	99.95	99.88

Table 10: Averages of instances with high and low levels of the show (no-show) levels.

Output variable	Low level	High level
Total profit	348354.02	275106.87
%sale Economy	80.83	67.65
%sale Economy Plus	84.70	73.21
%sale Business	57.39	51.48
%denied Economy	2.36	1.45
%denied Economy Plus	3.37	3.87
%denied Business	7.48	8.33
%average aircraft utilization	99.92	99.92

Table 11: Averages of instances with high and low levels of the show (no-show) levels.

Output variable	Low level	High level
Total profit	303622.76	319838.13
%sale Economy	80.99	67.49
%sale Economy Plus	86.20	71.71
%sale Business	59.12	49.76
%denied Economy	1.05	2.76
%denied Economy Plus	2.38	4.86
%denied Business	7.98	7.83
%average aircraft utilization	99.87	99.97

The results were analyzed statistically using an Analysis of Variance (ANOVA) assuming normal distributions of the output variables. The results are shown in Table 12.

Table 12: P-values for the ANOVA.

Output variable	Compensation fee	“Shows” proportion	Demand
Total profit	>0.05	0.008	0.038
%sale Economy	>0.05	>0.05	>0.05
%sale Economy Plus	0.002	0.001	0.001
%sale Business	>0.05	<0.001	<0.001
%denied Economy	>0.05	>0.05	>0.05
%denied Economy Plus	0.022	>0.05	0.027
%denied Business	>0.05	<0.001	<0.001
%average aircraft utilization	0.021	>0.05	0.015

The results obtained are mixed, but it can be observed that the no-shows and the demand have a significant impact on the Total profit and on the sales of the most expensive fare classes.

4 CONCLUSIONS

This study used a deterministic model approach to maximize total airline revenue, focusing primarily on overbooking, passenger no-shows, operating costs, demand, and capacity. The model also incorporated compensation fees for denying boarding, which influenced decision-making. The data estimated for this case study enabled a sensitivity analysis, which identified the parameters that significantly impact profit. After running the tests, it was determined that the compensation fee had minimal effect on profit, while show probability and demand were the most influential factors. Accurate demand forecasting and no-show rates are crucial for airlines to ensure positive profit. The main contributions of this paper are the inclusion of aircraft selection and ethical overbooking in a previously published optimization model, along with the use of a design of experiments to study the significance of some parameters on the total profit.

However, some limitations emerged in the study. The demand was based on fictional variations due to a lack of prior data. Airlines with access to historical flight data can use realistic variations and complement these with no-show rates to better estimate denied boarding. Another challenge was estimating fixed or operational costs, which were sourced from publicly available information. Additionally, many airlines have agreements with other carriers to accommodate denied boarding passengers, offering discounted fees in such cases.

Future work could explore more advanced scenarios, such as multiple flight legs, integrating different aircraft capacities, hubs, and nested or non-nested seat allocation. Additionally, varying the time range could also enhance the model’s applicability.

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