The Path to Maximizing Overbooking Profits for Low Cost Airlines

Shiqi Huang *

CATS Academy Boston, Boston, United States

* Corresponding Author Email: SH123757@catsboston.com

Abstract. Low-cost airlines commonly face revenue losses from passenger no-shows, typically ranging from 5% to 10%. To mitigate these losses, overbooking has become a core strategy. This paper uses AirAsia as a case study to explore how it maximizes revenue while balancing passenger experience through data-driven dynamic overbooking. The research method utilizes a case study, focusing on AirAsia's use of the Rokki platform for real-time data collection and the Kambr machine learning system for predictive modeling and dynamic adjustments. This platform can fully integrate multi-dimensional information such as flight booking data, passengers' historical travel records, and route passenger flow fluctuations, providing real-time data support for overbooking decisions. The study found that iterative optimization based on feedback mechanisms significantly improved load factors and financial performance while effectively reducing the risk of denied boarding. The conclusion is that intelligent overbooking strategies leveraging digital platforms and machine learning are crucial for low-cost airlines to maintain operational efficiency and market competitiveness.

Keywords: Low-cost airlines, overbooking, revenue management, machine learning.

1. Introduction

In recent years, airlines have faced a common challenge: not all passengers who purchase tickets will board on time. Due to reasons such as itinerary changes and missed flights, the proportion of "no-show passengers" (no-shows) is usually between 5% and 10%. For the aviation industry, which has limited seat resources and high operating costs, empty seats mean direct revenue losses. To reduce such losses, many airlines adopt an overbooking strategy, that is, selling more tickets than the actual number of seats on the flight to hedge the risk of no-shows.

For low-cost airlines, overbooking strategies are particularly important. Such companies rely on high seat utilization to spread fixed costs, thereby maintaining low fares and achieving profitability. As the largest low-cost airline in Asia, AirAsia relies heavily on refined seat configuration and revenue management in its operations. According to its 2024 financial report, it transported a total of 63.18 million passengers throughout the year, with an average passenger load factor of 89%, the highest level in recent years [1].

Although overbooking can help improve operational efficiency, it may also lead to problems such as denied boarding, which will hurt the passenger experience. Therefore, how to strike a balance between efficiency and passenger rights is a core issue that must be faced when formulating an overbooking strategy. With the development of digital technology, airlines are gradually moving away from their reliance on static historical data and turning to dynamic prediction and decision-making mechanisms driven by real-time data, thereby adjusting overbooking limits more accurately.

This paper aims to make up for the lack of details on the construction and operation of these dynamic mechanisms in existing research and analyzes the following two core issues: the main factors affecting airlines' overbooking decisions and how airlines use machine learning to optimize overbooking strategies to improve overall revenue in a dynamic environment. This study will use a case analysis method, combined with AirAsia's annual report and relevant academic literature, to explore how AirAsia implements dynamic overbooking with the help of digital platforms and algorithmic systems, and evaluate its effectiveness and potential limitations [2].

2. Drivers of Overbooking Policy

In the process of setting overbooking strategies, AirAsia comprehensively considered multiple variables, including historical no-show data, holiday periods, weather changes, and promotional activity responses. These variables were selected mainly because they have a significant statistical correlation with actual boarding rates. According to the analysis of Belobaba et al., no-show historical data is the core variable for building an overbooking model, and the higher show-keeping rate of holiday passengers also needs to be adjusted in the model weight [3]. In addition, bad weather and the high cancellation tendency of promotion-sensitive passengers have also been confirmed by the literature as important influencing factors [4]. AirAsia collects a large amount of passenger behavior data through Rokki and App platforms, which further enhances the model's ability to predict the probability of cancellation.

3. Implementation Strategy: Overbooking Mechanism Based on the Rokki Platform

3.1. Main Role

The Rokki platform is a core component of AirAsia's digital transformation strategy. In addition to providing Wi-Fi and entertainment services to passengers, it also undertakes the important functions of data collection and real-time analysis. Since 2018, AirAsia has cooperated with Google Cloud to introduce machine learning and artificial intelligence technologies in demand forecasting, pricing management and additional service optimization, aiming to achieve more refined operation management. The Rokki platform not only helps AirAsia provide passengers with seamless internet connectivity, rich entertainment content, and a convenient shopping experience onboard, but also continuously collects passenger interaction data, feeding key behavioral indicators into its revenue management models. This allows the prediction system to accurately identify dynamic changes in passenger cancellations, changes, and no-shows.

The platform's information collection and real-time transmission ensure accurate data updates at every stage of flight operations, empowering machine learning models to achieve point-in-time predictions and risk assessments of passenger "no-show rates."

Furthermore, Rokki platform data is used not only for passenger behavior analysis but also as a foundation for dynamic flight scheduling and resource allocation. By continuously monitoring real-time data, the revenue management system can flexibly adjust overbooking limits, dynamically respond to market demand and unexpected events, and maximize flight load factors and revenue. Furthermore, the platform's real-time feedback mechanism rapidly transmits actual boarding status, denied boarding incidents, and passenger compensation information, achieving a closed-loop data management system and ensuring the continuous updating and optimization of machine learning models.

3.2. Dynamic Adjustment Mechanism

AirAsia’s overbooking strategy has several key prediction nodes, which re-evaluate the no-show rate at 14 days, 7 days, 2 days and 1 hour before the flight departure, and dynamically adjust the overbooking amount accordingly. If the forecast shows a high boarding rate, the system will recommend lowering the overbooking amount or starting the rebooking incentive in advance; if the forecast boarding rate drops, the number of overbooked tickets will be increased accordingly to improve the passenger load factor. Since 2018, this mechanism has been continuously iterated and optimized, forming a closed-loop process of "prediction-feedback-correction", which occupies an important position in AirAsia's overall revenue management system [5].

4. Applying Machine Learning for Optimization

4.1. Specific Machine Learning System

After an in-depth exploration of AirAsia's overbooking policy mechanism, it was found that the Rokki platform is based on the cooperation of the Kambr system. In modern route revenue management, dynamic optimization of overbooking strategies is the key to improving revenue and operational efficiency for low-cost airlines. While the Rokki platform, as the foundational data collection and passenger interaction system for AirAsia's digital transformation, provides real-time support for passenger behavior and operational data, the core of the dynamic, intelligent optimization of overbooking strategies stems from the introduction and application of Kambr's Eddy revenue management software. Kambr, this advanced machine learning-driven revenue management system, leverages the rich data collected by Rokki and dynamically adjusts to multiple time periods and fluctuating factors, empowering AirAsia's overbooking strategies with scientific, flexible, and sustainable optimization capabilities.

4.2. Machine Learning-Driven Dynamic Overbooking Mechanism

First, Kambr's Eddy system intercepts and deeply mines multi-dimensional data collected from Rokki, booking platforms, flight operations databases, and other channels, including passenger purchase behavior, cancellation and change history, fare fluctuations, flight schedules, and seasonality, holidays, and weather. This data exhibits distinct time series characteristics and seasonal fluctuations, fully reflecting the complexity of the dynamic environment of aviation operations. Using powerful data fusion and feature engineering techniques, Kambr constructs a dynamic variable set, ensuring that its machine learning model can capture fluctuations in passenger attendance caused by factors such as holiday peaks, promotional events, and uncertain weather.

For example, during promotional events, if the system predicts a decrease in the no-show rate, it recommends reducing the overbooking allowance to mitigate the risk of denied boarding. If the number of refunds surges near departure, the system automatically increases the overbooking allowance and activates a standby passenger notification mechanism to avoid wasted resources.

The introduction of machine learning technology enables AirAsia to break away from the traditional static overbooking model and achieve dynamic optimization of its overbooking strategy. The model primarily utilizes rolling time series training and multivariate fusion to accurately predict no-show rates and drive multi-stage rolling adjustments to the overbooking strategy.

The specific advantage lies in its real-time understanding of passenger behavior and market fluctuations. It utilizes integrated algorithms such as XGBoost, random forests, and long short-term memory (LSTM) networks to comprehensively capture nonlinear relationships and temporal dependencies, improving prediction accuracy.

The prediction results are combined with reinforcement learning algorithms to form a dynamic overbooking decision-making framework. The system continuously adjusts the overbooking allowance at key points before flight departure and coordinates fare policies and rebooking incentives to address demand fluctuations and potential risks. This mechanism enhances the overbooking strategy's sensitivity and adaptability to market and passenger behavior, ensuring maximum revenue while appropriately controlling the risk of denied boarding.

4.3. Dynamic Feedback Mechanism and Model Self-Correction Optimization Process

Furthermore, Kambr leverages the personalized analysis capabilities of machine learning to support additional service recommendations and price strategy adjustments based on passenger characteristics and historical behavior. Integrating real-time customer interaction and behavioral data from the Rokki platform, AirAsia can dynamically adjust value-added services such as seat upgrades, baggage fees, and priority boarding, providing both a personalized experience for passengers and financial compensation for the overbooking strategy, creating a closed loop where overbooking and additional revenue complement each other.

The Kambr platform also establishes a "prediction-execution-feedback" closed-loop system, where actual flight boarding data, denied boarding, and compensation records are fed back into the system in real time to drive continuous model training and optimization. This allows the machine learning model to continuously self-correct, overcoming the shortcomings of traditional static models, which often experience reduced prediction accuracy during periods of significant market volatility, and ensuring the efficient and accurate operation of the dynamic overbooking strategy.

First, the system collects real-time boarding data for each flight, including key information such as the actual number of passengers boarding, denied boarding incidents, passenger complaints and compensation. This data is compared with the predicted no-show rate data to quickly identify prediction errors and deviations. This process is not limited to a single flight but also covers cluster data of the same route in different time periods and evaluates the model prediction performance in a hierarchical and multi-dimensional manner.

Secondly, the feedback data is automatically written into the training database to participate in the parameter adjustment and weight update of the next round of the machine learning model. Incremental learning technology is used to avoid training from scratch, significantly improving the model update speed and the ability to respond to real-time market changes [6]. The system uses gradient descent and other optimization algorithms to re-weight features with large errors, gradually correcting the deviations and deficiencies in past predictions.

During the model correction process, new feature variables are continuously introduced, such as the recent trend of passenger cancellation and rebooking, the effect of emerging promotional activities, or temporary weather forecast information, to keep the model highly sensitive to environmental changes. This dynamic feature expansion ensures that the prediction continues to fit the latest passenger behavior patterns and market conditions, rather than remaining in a historical fixed pattern.

At the same time, the decision-making level also adjusts the strategy parameters synchronously. The reinforcement learning algorithm uses the updated model output to evaluate the profit and risk trade-offs under different oversold levels and intelligently selects the optimal action [7]. The system can even simulate the profit results of multiple time periods and multiple scenarios, predict possible future situations, and then perform forward-looking adjustments, thereby improving the scientific nature and stability of the overall strategy [8].

AirAsia also has a dedicated manual monitoring and intervention mechanism to quickly respond to abnormal data and abnormal behavior. If the model shows excessive prediction deviation or abnormal fluctuation, the operations team can intervene through the background analysis tool to adjust parameters or temporarily formulate emergency measures. This collaboration between humans and intelligence enhances the reliability of the system [9].

5. The Impact of Overbooking on Improving Passenger Load Factor and Revenue

According to the 2024 financial report released by Capital A (AirAsia's parent company), AirAsia's annual passenger traffic increased by 11% year-on-year, while the number of available seats increased by only 10%. The overall passenger load factor reached 89%, significantly higher than the low level during the epidemic (68% in 2021) and higher than the stable range before the epidemic (approximately 70% to 75%). The load factor reached a high of 90% in the first quarter of 2024 and has continued to rise annually from 68% to 89% from 2021 to 2024, demonstrating the positive impact of the overbooking strategy in improving seat utilization and marginal revenue. Financial performance also increased from RM1,836 million to RM14,693 million. Although AirAsia has not yet disclosed the specific percentage of no-shows, combined with its continuously optimized forecasting model and policy feedback system, it is reasonable to infer that its overbooking mechanism has played a key role in reducing empty seats and improving operational efficiency [10].

6. Conclusion

Long-term operation has demonstrated that this feedback-driven, self-correcting system not only improves forecast accuracy and reduces operational losses caused by over- or under-booking, but also effectively reduces passenger rejection rates and the resulting customer relationship risks. The dynamic, iterative optimization of the model and policy significantly ensures that the overbooking strategy maintains optimal performance despite complex and volatile flight demand and market conditions, becoming the core technical support for AirAsia's efforts to enhance operational efficiency and market competitiveness.

By integrating data from the Rokki platform with Kambr's machine learning-driven revenue management system, AirAsia has built a dynamic overbooking optimization platform that integrates rolling forecasts, seasonality and multi-factor fluctuation capture, dynamic decision-making through reinforcement learning, multi-level customer segmentation, and personalized value-added services. With the continued enrichment of data sources, continuous iteration of model algorithms, and deeper integration with business needs, this dynamic machine learning optimization platform will continue to evolve, driving low-cost airlines towards more intelligent and efficient operations.

For low-cost airlines, overbooking is not only a means of compensating for empty seats but also a crucial tool for improving revenue management efficiency. Future strategy development should prioritize the integration of multi-dimensional data, such as passenger purchasing habits, holiday travel patterns, and the impact of weather and promotions, to enhance forecast reliability. Secondly, dynamic adjustment mechanisms are more responsive to market fluctuations than fixed overbooking limits. Forecasts should be continuously revised at different time points to mitigate the risk of over- or under-booking. Furthermore, appropriate compensation measures and personalized services can mitigate the negative impact on the passenger experience in the event of a denied boarding. Finally, while data and algorithms can provide powerful support, human judgment is still needed to intervene in special circumstances to balance revenue goals and service quality.

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