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Revenue Management Strategies in Airline Industry: A Literature Review

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Abstract. The airline industry has rapidly evolved, fostering intense competition among companies. This competition drives airlines to formulate strategies for revenue maximization, giving rise to Revenue Management. This literature review spans the past 13 years, examining the development of Airline Revenue Management methods. By analyzing 22 journals with at least Q2 and SINTA 2 indexing, three primary scopes emerge: Quantity Decision, Pricing Decision, and Structural Decision. Airlines predominantly employ dynamic pricing and programming to optimize revenue by adapting to ongoing changes. The development trend in Airline Revenue Management indicates a shift towards faster and more accurate processing through increased integration with simulation and algorithm programming. This paper identifies the three main scopes involved in revenue management strategies and explores the diverse approaches airlines take to optimize income. Notably, dynamic pricing and programming remain prevalent methods, adapting to changing decision variables. The evolving landscape emphasizes integration with advanced technology for efficient processing. The study utilizes numerical and case studies to exemplify the ongoing development of Airline Revenue Management methods within this dynamic industry.

Keyword: Airlines, Price Decision, Quantity Decision, Revenue Management, Structural Decision

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1. Introduction

The airline sector, predominantly situated in the service industry, has witnessed substantial growth marked by increased competition, rising passenger numbers, and expanding flight carrier options. Fierce competition necessitates strategic revenue maximization efforts by each airline [1].

Despite the industry's rapid expansion, it faces persistent challenges such as inadequacies in ticket pricing, neglect of simultaneous ticket availability considerations, pricing adjustments based on competitors, suboptimal booking limits, customer behaviors causing delays in ticket purchases anticipating price drops, and instances where pre-booked customers are denied boarding due to

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overbooking. The overarching challenge is to sell the right seats to the right customers at the right prices and times.

The widespread adoption of Revenue Management (RM) has become imperative for airlines striving to maintain profitability. Initially gaining prominence through successful implementation by American Airlines, RM practices contribute to a revenue increase of around 4–5%, comparable to the total profitability of many airlines in a favorable fiscal year [2].

Addressing industry challenges, RM in the airline sector aims to optimize total revenue through dynamically controllable ticket sales. At its core, RM involves managing seat allocations across different fare groups [3]. While airlines prioritize accommodating higher-fare customers, demand uncertainty prompts consideration for filling seats with lower-fare customers, aiming to mitigate opportunity costs related to unoccupied seats. The challenge lies in finding the optimal balance between selling lower-fare seats and reserving capacity for potential higher-fare passengers [1]. The philosophy is to sell tickets at the right time and offer appropriate fares to the right customers before departure [3].

While the price and demand of a product are intricately connected, they are rarely optimized together, despite the potential for increased revenue. In the realm of Revenue Management literature, there is a prevalent assumption that either prices are fixed and capacity control is conducted under this premise, or capacity allocation is considered fixed with only price optimization. This is often attributed to the increased complexity that arises when both prices and booking limits are treated as variables. Additionally, the coordination of previously independent pricing and capacity allocation systems is deemed challenging and may not be perceived as worthwhile due to the significant efforts involved [4].

Research in the airline industry typically centers on forecasting, overbooking, seat inventory control, and fare pricing. RM methods encompass decision-making on demand management, categorized into structural decisions, price decisions, and quantity decisions. Structural decisions focus on determining the sales format to be used, such as the pricing for advertisements, negotiations, or auctions. Structural decisions involve determining sales formats, market segmentation, trade conditions, and product bundling [5].

Price decisions address setting prices, individual offer prices, and considerations for reducing prices or applying discounts. Quantity decisions revolve around accepting or rejecting buyer offers, allocating capacity to different price classes, and deciding when to withhold a product from the market and sell it later [5].

This article presents a literature review on RM in the airline industry, drawing from 22 research papers globally. Key topics covered include industry issues, resolution methods, problem constraints, and research types (numerical studies or case studies). The information is categorized based on decision scopes, encompassing quantity, pricing, and structural decisions.

2. Research Method

The method employed in crafting this article is a literature review, involving the exploration of both international and national literature through the use of the Google Scholar database. The literature review process consists of three stages: planning, conducting, and reporting [6].

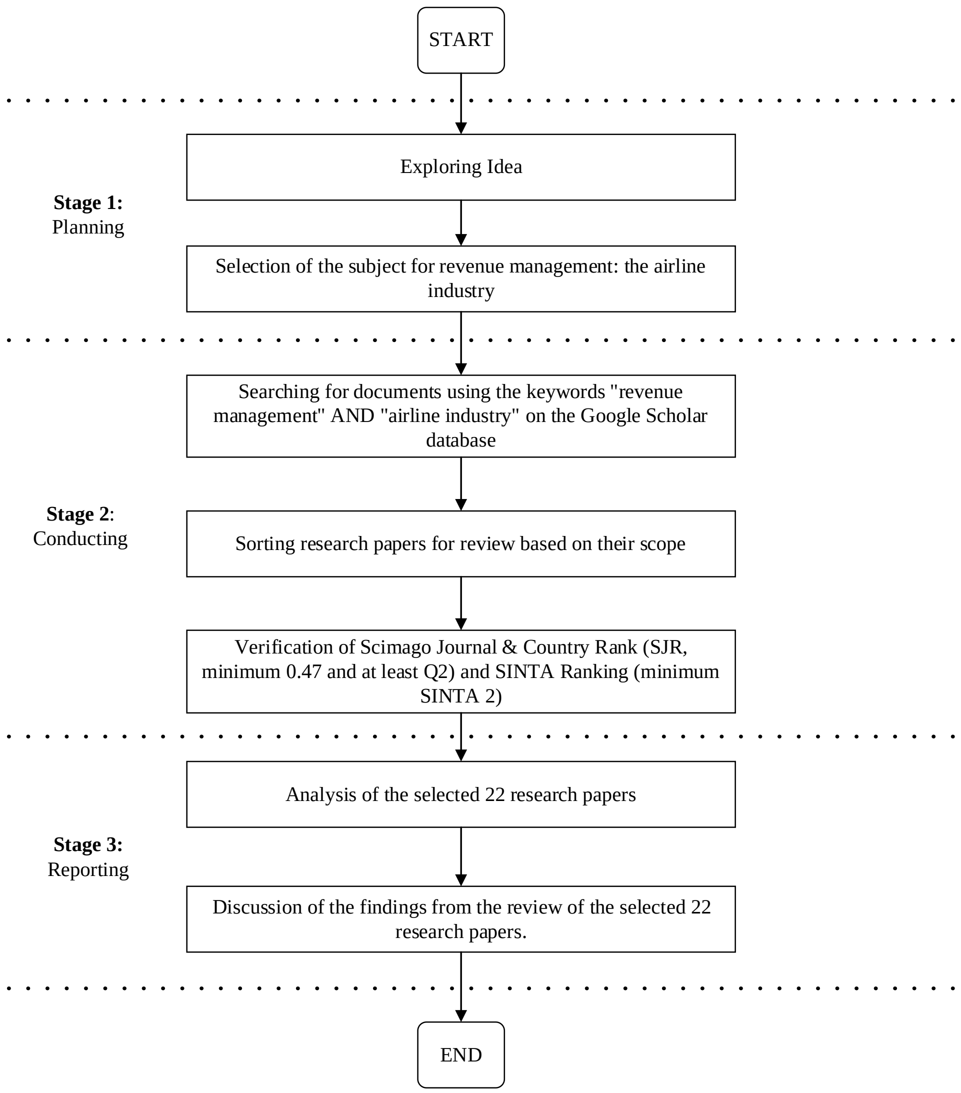

Figure 1 Literature Review Method

The initial stage of this literature review involves exploring ideas related to revenue management in the field of Industrial Engineering, encompassing news, research findings, and previous literature reviews. This exploration aims to derive the concept of "revenue management in the airline industry." The second stage is the conducting phase, commencing with the search for research papers using the keywords "revenue management" AND "airline industry" on Google Scholar. This search yielded a total of 6,880 research papers. Subsequently, the papers were sifted based on their relevance to revenue management in the airline industry, focusing on structural decisions, price decisions, and quantity decisions. The selected research papers are from reputable journals with a Scimago Journal & Country Rank (SJR Rank) of at least 0.47, falling within the

Q2 quartile, and reputable national journals indexed in SINTA 2. A total of 22 research papers published between 2009 and 2023 were chosen.

The third stage involves reporting and begins with the analysis of the selected twenty research papers. This analysis aims to identify key aspects to be discussed in the literature review, encompassing topics related to the implementation of revenue management in the airline industry. The discussion in this stage revolves around the strategies and methods developed to achieve the goal of optimizing Airline Revenue Management.

3. Results and Discussion

In this section, we have identified and selected 22 research papers pertinent to revenue management within the airline industry for comprehensive review. The initial segment will offer a broad perspective on the primary research domain of revenue management in the airline industry, emphasizing key research aspects derived from the literature review. Following this, subsequent sections will present individual literature reviews for each dimension pertaining to revenue management within the airline industry.

3.1. Overview of Revenue Management in the Airline Industry

Exploration into revenue management within the airline sector focuses on three primary domains, with the initial area centered on decisions related to quantity. In the quantity decision area, the focus is on capacity control, network management, and overbooking. The second area is pricing decision. Within the pricing decision realm, discussions revolve around determining optimal prices for various categories, individual pricing offers, and the like. Some methods employed in pricing include dynamic pricing and stochastic dynamic pricing. The third area is the structural domain. Structural aspects discussed include the sales format used, segmentation mechanisms employed, and so forth. Table 1 illustrates the research focus from the entirety of the reviewed literature. Figure 2 depicts the paper scope with detailed breakdowns: 10 papers investigate quantity decision, 6 focus on pricing, 2 cover both quantity and structural decision, 1 explores pricing and structural decision, 2 delve into quantity and pricing, and 1 examines quantity, pricing, and structural decision. The research years are mapped in Figure 2.

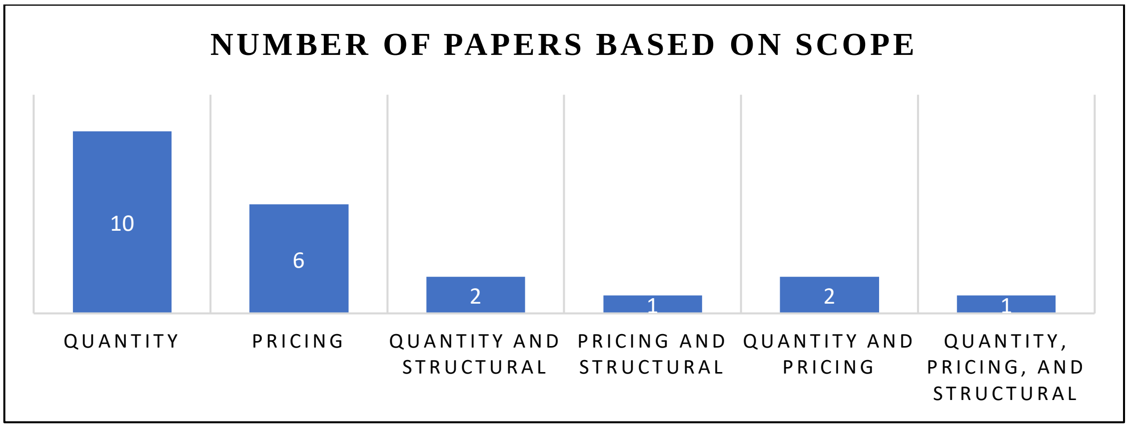

Figure 2 Number of Research Papers Based on Scope

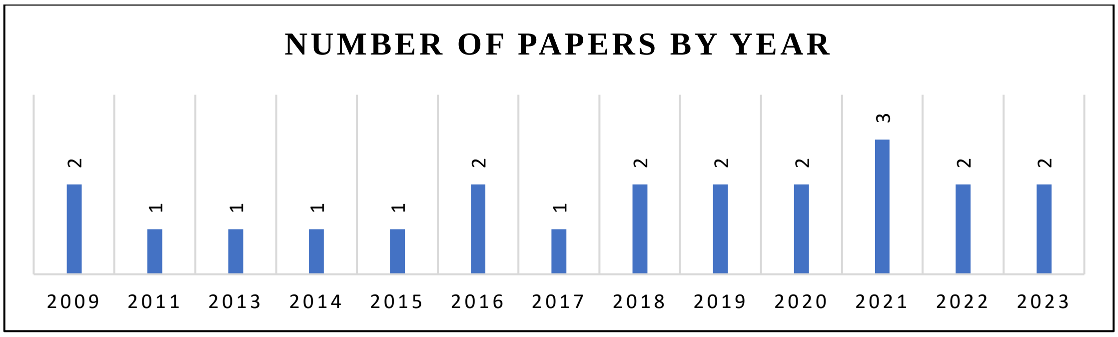

Figure 3 Number of Research Papers by Year

Table 1 Research Papers Classification

No	Author(s) (Year)	Scope			Method	Numerical/Case Study
		Price	Quantity	Structural		
1.	Birbil et al. (2009) [7]		✓		Classical Static and Dynamic Single-Leg Seat Allocation Models	Numerical
2.	Zhang and Chooper (2009) [8]	✓		✓	Markov Decision Process and Heuristic	Numerical
3.	Huang and Liang (2011) [2]		✓	✓	Dynamic Programming	Numerical
4.	Rusdiansyah et al. (2013) [9]	✓			Dynamic Pricing	Numerical
5.	Aslani et al. (2014) [10]	✓		✓	Heuristic and Simulation	Numerical
6.	Otero and Akhavan (2015) [11]	✓			Stochastic Dynamic Programming	Case Study
7.	Fu et al. (2016) [12]		✓		Deterministic And Tractable Mixed Integer LP	Case Study
8.	Grauberger and Kimms (2016) [4]	✓	✓		Algorithmic Game Theory dan Nash Equilibrium	Numerical
9.	Somboon and Amaruchkul (2017) [13]		✓		Stochastic Programming	Numerical
10.	Kyparisis and Koulamas (2021) [14]	✓	✓		TCARM (Two Cabin Airline Revenue Management)	Numerical
11.	Wang et al. (2018) [15]		✓		Dynamic Programming	Numerical
12.	Selcuk and Avsar (2019) [16]	✓			Dynamic Pricing	Numerical
13.	Fard et al. (2019) [17]		✓		Dynamic Programming	Numerical
14.	Venkataraman et al (2020) [18]		✓	✓	Dynamic Programming, Mathematical Programming	Numerical
15.	Sahin and Ertugrul (2020) [19]		✓		TRB (Total Revenue Boundaries)	Numerical
16.	An et al. (2021) [1]		✓		Linear Programming dan Genetic Algorithm	Numerical
17.	Imai et al (2021) [20]		✓		Stochastic Programming	Numerical
18.	Koc and Arslan (2021) [21]	✓			Multivariable Long Short-term Memory	Case Study
19.	Li et al. (2022) [3]		✓		Deterministic Integer Programming Model dan Stochastic Integer Program	Numerical
20.	Fukushi et al. (2022) [22]	✓	✓	✓	Discrete Choice Model dan Simulation	Case Study
21.	Thirumuruganathan et al. (2023) [23]	✓			Machine Learning with Price Elasticity Model	Numerical
22.	He at al. (2023) [24]		✓		Long Short-Term Memory	Numerical

3.2. Quantity Decision

After conducting a literature review, out of the 15 literatures that explored quantity decision in the airline industry, the literature generally focuses on overbooking and capacity allocation. Only one scholarly article addresses booking limits, where researchers determine the optimal booking limit with limited data information [1].

Capacity allocation stands out as a pivotal approach to enhance revenue in the airline industry. Scholarly articles exploring this topic exhibit differences in the strategies employed, methods utilized, and issues under examination. The determination of capacity allocation is contingent on specific conditions, methods applied, and strategies executed, all contributing to an overall improvement in the company's revenue. For example, deciding on capacity allocation through a multi-channel distribution not only boosts revenue but also effectively cuts down on distribution costs across channels [15].

Determining capacity allocation by considering the nature of consumer reservations also influences revenue. The determination of optimal capacity allocation can take into account the dynamics of group behavior concerning cancellations and refunds. The research findings indicate an increase in the total generated revenue as a result [18]. Determining capacity allocation for cargo planes is also essential to boost revenue. Researchers also determine container slots with a minimum quantity commitment under uncertain demand and find an expected revenue increase [12].

The development of seat capacity determination in Revenue Management relies heavily on demand data in each class. Not only does this data change over time, but data limitations also render the determination of each class's capacity irrelevant. In the studies by [20] and [3], they transform the deterministic model in conventional Revenue Management into a stochastic model to model uncertainty. Based on numerical calculations, both obtain maximum revenue compared to conventional Revenue Management models like EMSR B and Littlewood. However, practical application depends significantly on modeling randomness in historical data. This poses a challenge in a research, where data limitations introduce bias into the modeling. To address this, researchers predict insufficient data using linear programming and genetic algorithms [1].

In addition to suitable capacity allocation, a tactic employed to boost revenue within the airline sector involves overbooking. Scholars advocate the utilization of dynamic programming for implementing overbooking strategies in airlines. The findings offer insights into how airlines can select strategies to pursue optimal solutions customized to their specific needs [17]. In parallel, some researchers integrate two fundamental revenue management strategies for airlines overbooking and seat inventory control. The performance of a two-class overbooking model surpasses that of fixed reservation limit policies [13].

Another way to enhance revenue in the airline industry is by forecasting demand for specific airlines. Precise demand prediction is increasingly crucial for airlines to navigate external competition and boost revenue efficiently. To achieve more efficient computation, machine learning algorithms such as Long Short-Term Memory (LSTM) can be employed. Results from simulations, based on an anonymized dataset of around 20,000 records for a particular route, highlight the superior performance of the suggested model compared to traditional methods. It achieves a mean absolute percentage error (MAPE) that is significantly 45.1% lower than alternative techniques, emphasizing its enhanced predictive accuracy. This research not only showcases the relevance of deep learning algorithms in airline demand forecasting but also emphasizes their capacity to enable airlines in effectively managing demand-related risks and optimizing revenue management strategies [24].

3.3. Price Decision

Setting prices plays a pivotal role in augmenting revenue within the airline industry. Six academic papers delve into the establishment of effective pricing strategies to elevate revenue for airlines. The distinctions among these studies lie in the methodologies employed and the formulation of precise pricing strategies that align with real-world conditions. Researchers suggest a stochastic dynamic pricing model, incorporating phase-type distributions and renewal processes to model the time intervals between two customers booking tickets and the likelihood of customers purchasing tickets. The findings indicate an average revenue increase of 31 percent [11]. Furthermore, there is dedicated research specifically aimed at examining the primary sources of unjust pricing among transportation operators, utilizing results derived from a developed simulator [10].

The methods for pricing determination in Revenue Management have evolved, considering both direct and indirect influences. Conventional pricing determination in revenue management, which only considers deterministic and stochastic factors, is no longer effective in adapting to changes. To address this, current research focuses on how pricing in Revenue Management can be reliable amid constant changes. Two literatures, [9] and [16] develop pricing models with Dynamic Pricing, each using different methods to address various variables. These variables need to be modeled before being incorporated into Dynamic Pricing for each scenario.

The accuracy of modeling these variables is crucial for the application of Dynamic Pricing in Revenue Management because pricing in dynamic pricing will continually change based on the unfolding scenarios. To address this, authors develop machine learning by combining multiple algorithms to analyze trend developments as scenario variables in Dynamic Pricing. With the speed and accuracy of machine learning, it can be assumed that the evolution of Revenue Management will move towards the utilization of Artificial Intelligence [21].

Utilizing machine learning presents an opportunity to identify customers transitioning from economy to premium class and ascertain an acceptable price range. The Price Elasticity Model (PREM) stands out as a machine learning algorithm capable of addressing this challenge. Through a simulation involving 64.3 million flight bookings and 14.1 million email offers spanning three years, reflecting real-world data, the incorporation of PREM is shown to reduce approximately 1.12 million (7.94%) irrelevant customer email messages. Furthermore, it forecasts a surge of

72,200 (37.2%) in accepted offers and an estimated $72.2 million (37.2%) increase in revenue. Researchers have also classified customers into three segments: (1) Never Upgrades, denoting those consistently declining upgrade offers; (2) Upgrade Lovers, representing individuals frequently opting for upgrades; and (3) Upgrade Lover Lookalikes, a group lacking historical upgrade records but exhibiting characteristics akin to those who typically choose to upgrade. This analysis delves into the implications of these segments for airline companies and the broader travel and tourism industries [23].

3.4. Structural Decision

The determination of strategies through structural decision-making is established after setting prices and/or quantities to maximize revenue based on competition. The optimization of revenue management is determined by strategies after obtaining optimal prices or quantities while considering competitors. There is a research that models with Markov and heuristics to determine which prices and strategies are chosen to achieve optimal revenue [8].

Meanwhile, in the research by other researchers, they consider which classes and capacities to adopt in facing competition with competing flights scheduled at the same time. However, structural decision calculations require a significant amount of time due to data processing and collection. In intense competition, speed becomes a competitive advantage in responding to changes [2].

The integration of Revenue Management in computational processing is becoming a trend to enhance decision-making speed. Authors model competition in Network Revenue Management with game theory algorithms modeled through computation, resulting in greater speed and accuracy in modeling competition and making decisions to obtain optimal revenue [4]. To enhance accuracy, other authors demonstrate simulations of changes in factors influencing airline revenue management, such as competitors, customer characteristics, demand nature, supply nature, etc. This aims to provide insights into the impact of parameter changes to assist decision-making in optimizing revenue [22].

4. Conclusion

The application of revenue management in the airline sector, aimed at optimizing revenue, involves three key aspects: quantity decision, pricing decision, and structural decision. Quantity decision encompasses strategies like overbooking, capacity allocation, and booking limits, often implemented through dynamic and stochastic methods. Pricing decision also holds significance in revenue enhancement, with competitive pricing strategies developed through dynamic, stochastic, and machine learning algorithms to compete effectively with rivals. Meanwhile, structural decision involves determining maximum quantity or price under specific conditions. The adoption of machine learning is emerging as a trend to expedite decision-making processes and enhance accuracy. The airline industry's unique and dynamic challenges in revenue management necessitate problem-solving through diverse methods, techniques, formulas, and approaches. Consequently, each airline adopts distinct strategies to optimize revenue. Revenue optimization involves seat allocation, pricing determination, overbooking strategies, discount determination, class assignment, and other related factors.

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REFERENCES

[1] J. An, A. Mikhaylov, and S.-U. Jung, "A Linear Programming approach for robust network revenue management in the airline industry," *J. Air Transp. Manag.*, vol. 91, p. 101979, Mar. 2021, doi: 10.1016/j.jairtraman.2020.101979.

[2] K. Huang and Y.-T. Liang, "A dynamic programming algorithm based on expected revenue approximation for the network revenue management problem," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 47, no. 3, pp. 333–341, May 2011, doi: 10.1016/j.tre.2010.11.005.

[3] Y. Li, A. Mahmoudzadeh, and X. B. Wang, "Airlines Seat Pricing with Seat Upgrading," *Multimodal Transp.*, vol. 1, no. 4, p. 100054, Dec. 2022, doi: 10.1016/j.multra.2022.100054.

[4] W. Grauberger and A. Kimms, "Airline revenue management games with simultaneous price and quantity competition," *Comput. Oper. Res.*, vol. 75, pp. 64–75, Nov. 2016, doi: 10.1016/j.cor.2016.05.008.

[5] K. T. Talluri and G. J. Ryzin, *The Theory and Practice of Revenue Management*. Springer Science+Bussiness Media, Inc., 2004.

[6] B. Kitchenham, "Procedures for Performing Systematic Reviews," *Dep. Comput. Sci. Keele Univ.*, pp. 1–26, 2004.

[7] Ş. İ. Birbil, J. B. G. Frenk, J. A. S. Gromicho, and S. Zhang, "The Role of Robust Optimization in Single-Leg Airline Revenue Management," *Manag. Sci.*, vol. 55, no. 1, pp. 148–163, Jan. 2009, doi: 10.1287/mnsc.1070.0843.

[8] D. Zhang and W. L. Cooper, "Pricing substitutable flights in airline revenue management," *Eur. J. Oper. Res.*, vol. 197, no. 3, pp. 848–861, Sep. 2009, doi: 10.1016/j.ejor.2006.10.067.

[9] A. Rusdiansyah, R. Dwi A. P., and N. Puspitasari, "Model Dynamic Pricinguntuk Penetapan Harga Tiket Pesawat Terbang Berbasis Waktu dan Persediaan Kursi dengan Mempertimbangkan Keputusan Kompetitor," *J. Tek. Ind.*, vol. 15, no. 1, pp. 45–56, May 2013, doi: 10.9744/jti.15.1.45-56.

[10] S. Aslani, M. Modarres, and S. Sibdari, "On the fairness of airlines' ticket pricing as a result of revenue management techniques," *J. Air Transp. Manag.*, vol. 40, pp. 56–64, Aug. 2014, doi: 10.1016/j.jairtraman.2014.05.004.

[11] D. F. Otero and R. Akhavan-Tabatabaei, "A stochastic dynamic pricing model for the multiclass problems in the airline industry," *Eur. J. Oper. Res.*, vol. 242, no. 1, pp. 188–200, Apr. 2015, doi: 10.1016/j.ejor.2014.09.038.

[12] Y. Fu, L. Song, K. K. Lai, and L. Liang, "Slot allocation with minimum quantity commitment in container liner revenue management: A robust optimization approach," *Int. J. Logist. Manag.*, vol. 27, no. 3, pp. 650–667, Nov. 2016, doi: 10.1108/IJLM-06-2013-0075.

[13] M. Somboon and K. Amaruchkul, "Applied Two-Class Overbooking Model in Thailand's Passenger Airline Data," *Asian J. Shipp. Logist.*, vol. 33, no. 4, pp. 189–198, Dec. 2017, doi: 10.1016/j.ajsl.2017.12.002.

[14] G. J. Kyparisis and C. Koulamas, "Optimal pricing and seat allocation for a two-cabin airline revenue management problem," *Int. J. Prod. Econ.*, vol. 201, pp. 18–25, Jul. 2018, doi: 10.1016/j.ijpe.2018.04.021.

[15] W. Wang, O. Tang, and J. Huo, "Dynamic capacity allocation for airlines with multi-channel distribution," *J. Air Transp. Manag.*, vol. 69, pp. 173–181, Jun. 2018, doi: 10.1016/j.jairtraman.2018.02.006.

[16] A. M. Selçuk and Z. M. Avşar, "Dynamic pricing in airline revenue management," *J. Math. Anal. Appl.*, vol. 478, no. 2, pp. 1191–1217, Oct. 2019, doi: 10.1016/j.jmaa.2019.06.012.

[17] F. A. Fard, M. Sy, and D. Ivanov, "Optimal overbooking strategies in the airlines using dynamic programming approach in continuous time," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 128, pp. 384–399, Aug. 2019, doi: 10.1016/j.tre.2019.07.001.

[18] S. V. Venkataraman, A. Kaushik, and S. Mishra, "A network group booking model for airline revenue management," *J. Model. Manag.*, vol. 16, no. 3, pp. 861–903, Jul. 2021, doi: 10.1108/JM2-06-2020-0175.

[19] R. Sahin and A. E. Ertugrul, "A new approach for airline revenue management: total revenue boundaries," *Pressacademia*, vol. 9, no. 2, pp. 62–67, Jun. 2020, doi: 10.17261/Pressacademia.2020.1214.

[20] M. Imai, T. Sato, and T. Shiina, "Revenue management problem considering overbooking in the aviation industry," in *2021 10th International Congress on Advanced Applied Informatics (IIAI-AAI)*, Niigata, Japan: IEEE, Jul. 2021, pp. 855–860. doi: 10.1109/IIAI-AAI53430.2021.00149.

[21] I. Koc and E. Arslan, "Dynamic ticket pricing of airlines using variant batch size interpretable multi-variable long short-term memory," *Expert Syst. Appl.*, vol. 175, p. 114794, Aug. 2021, doi: 10.1016/j.eswa.2021.114794.

[22] M. Fukushi, F. Delgado, S. Raveau, and B. F. Santos, "CHAIRS: A choice-based air transport simulator applied to airline competition and revenue management," *Transp. Res. Part Policy Pract.*, vol. 155, pp. 297–315, Jan. 2022, doi: 10.1016/j.tra.2021.11.010.

[23] S. Thirumuruganathan, N. A. Emadi, S. Jung, J. Salminen, D. R. Robillos, and B. J. Jansen, "Will they take this offer? A machine learning price elasticity model for predicting upselling acceptance of premium airline seating," *Inf. Manage.*, vol. 60, no. 3, p. 103759, Apr. 2023, doi: 10.1016/j.im.2023.103759.

[24] H. He, L. Chen, and S. Wang, "Flight short-term booking demand forecasting based on a long short-term memory network," *Comput. Ind. Eng.*, vol. 186, p. 109707, Dec. 2023, doi: 10.1016/j.cie.2023.109707.