



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 11, November 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.524

 9940 572 462

 6381 907 438

 ijirset@gmail.com

 www.ijirset.com

Dynamic Pricing for Airline Tickets Using Reinforcement Learning and Game Theory

Kavya M B, Kusuma K, Umesha S

U.G. Student, Department of Computer Engineering, CIT, Gubbi, Tumkuru India

U.G. Student, Department of Computer Engineering, CIT, Gubbi, Tumkuru, India

Associate Professor, Department of Computer Engineering, CIT, Gubbi, Tumkur, India

ABSTRACT: The pricing of flight tickets plays a pivotal role in airline operations, customer satisfaction, and the sustainable growth of the air transportation sector. While significant research exists on ticket pricing strategies, many approaches overlook the integration of multiple factors and continuous decision-making processes. This study introduces an innovative game-theoretic framework using reinforcement learning to model sequential pricing strategies for competing flights. The model defines the pricing process as a sequential game, where the action space corresponds to pricing decisions, and the state space represents distinct decision points. Intelligent agents maximize profits by considering factors such as market demand, ticket supply, and passenger purchasing behaviours. Simulation results demonstrate that the agents' pricing strategies stabilize quickly, leading to Nash equilibrium solutions validated through utility function analysis. Findings indicate that revenue increases with stronger passenger preferences, decreases with higher demand sensitivity, and rises with greater supply sensitivity. This research offers a dynamic and comprehensive solution to ticket pricing and provides new insights into optimizing airline revenue management across multiple decision points.

KEYWORDS: Dynamic Pricing ,Reinforcement Learning ,Airline Revenue Management ,Flight Ticket Pricing.

I. INTRODUCTION

The rise of high-speed rail has significantly increased competition in the domestic passenger transportation market, pushing airlines to adopt innovative strategies to attract customers and stay competitive. Since flight tickets are a primary revenue source for airlines, their pricing strategies are crucial. Setting ticket prices too low results in direct financial losses, while excessively high prices reduce market demand, leading to unsold seats and decreased revenue. To ensure sustainable growth and maintain a competitive edge, airlines must implement pricing strategies that not only optimize profitability but also provide consumers with more options.

However, current pricing strategies exhibit notable shortcomings. Many airline administrators rely heavily on subjective judgment, leading to inconsistent and rudimentary approaches that lack precision. This overreliance hinders their ability to accurately predict market trends and often results in reactive strategies that mimic competitors. Addressing these issues requires the development of robust mathematical models that enhance prediction accuracy and adapt effectively to dynamic market conditions.

Ticket pricing typically considers fixed and variable costs alongside market demand. Airlines classify passengers based on their price sensitivity, with higher-priced tickets targeting fewer sensitive customers and lower-priced tickets appealing to those more price-conscious. In highly competitive markets, airlines monitor competitors' pricing strategies on similar routes through ticketing platforms and respond promptly to price reductions, particularly during periods of low demand. The fluctuating nature of market demand further complicates the process, as the pricing decisions of one airline influence the strategies of others, turning ticket pricing into a sequential game problem.

Sequential games involve multiple decision points where participants must account for their strategies and anticipate the actions of others to optimize outcomes. Decisions made at one point influence subsequent actions, adding layers of complexity to the problem. This paper addresses these challenges by proposing a comprehensive ticket pricing model that incorporates costs, demand, and passenger preferences. Using a game-theoretic framework with intelligent agents, the model simulates the sequential pricing process through reinforcement learning. It explores the interactions between competing airlines and transforms the pricing challenge over the entire sales period into a multi-period game framework. Simulations validate the model's practicality, providing new insights into optimizing ticket pricing strategies.

The structure of the paper is as follows: a review of related work introduces the context, followed by an in-depth discussion of the ticket pricing game model and the proposed reinforcement learning solution. Simulation results are presented to demonstrate the model's effectiveness, and the study concludes with insights and directions for future research.

The remainder of this paper is structured as follows: Section II reviews related work. Section III introduces the ticket pricing game model. Section IV outlines the pricing solution using reinforcement learning. Section V presents the results of simulation experiments. Finally, Section VI concludes the study and highlights future research directions.

II. RELATED WORK

This section reviews related work on reinforcement learning, game theory, and flight ticket pricing.

A. Reinforcement learning

Reinforcement learning involves an agent that interacts with its environment, selects actions based on the current state, and receives rewards to guide decision-making. Actions can be deterministic or stochastic, impacting both rewards and the environment's state. Q-learning, a value-based algorithm, is widely used in dynamic environments, offering significant advantages over traditional methods. Recent advancements, such as double Q-learning and deep Q-learning, have further expanded its applications, particularly in complex real-world scenarios.

B. Game Theory and Reinforcement Learning

Game theory explores strategic interactions among decision-makers, often combined with reinforcement learning for optimization in dynamic systems. For instance, a Stackelberg game-based pricing mechanism optimized resource allocation in edge clouds, while a two-stage deep reinforcement learning approach addressed computation offloading in partially observable environments. However, these studies often overlooked sequential decision-making, a key aspect of dynamic pricing strategies like flight ticket pricing.

C. Flight Ticket Pricing

In aviation, ticket pricing involves balancing conflicts of interest between airlines and passengers. Game theory has been applied to model competition and optimize pricing strategies. Prior work includes a demand-price model analysing competition between two airlines and a spokes model exploring passenger preferences in a free-sale environment. However, these models often oversimplified decision-making by ignoring sequential decisions and the impact of demand on pricing.

This study extends these approaches by utilizing Q-learning to optimize ticket prices throughout the sales period. Prices are dynamically adjusted daily based on market conditions, addressing sequential decision-making challenges and incorporating factors like market demand, passenger preferences, and competition. This framework offers a more comprehensive and adaptive solution to airline ticket pricing.

III. METHODOLOGY

The methodology for optimizing ticket pricing for a single flight involves applying reinforcement learning (RL) to dynamically adjust prices over the flight's sales period. The process begins with modeling the intricate relationship between ticket price, market demand, and revenue generation. At each decision point, the airline sets ticket prices sequentially with the goal of maximizing overall revenue while accounting for varying demand at different price levels. Market demand is assumed to decrease as ticket prices increase, and sales are distributed based on passengers' sensitivity to price changes, reflecting real-world booking behaviors and market conditions.

To achieve this dynamic optimization, the Q-learning algorithm, a type of RL, is used to make informed pricing decisions. The sales period is divided into discrete time steps, each representing a decision on what price to set for tickets at that particular moment. At each step, the algorithm evaluates various potential pricing strategies, simulating the outcomes and adjusting the pricing decisions based on the revenue impact of previous actions. This iterative learning process allows the algorithm to continuously update its model by factoring in changes in demand, the remaining number of available seats, and the evolving competitive landscape.

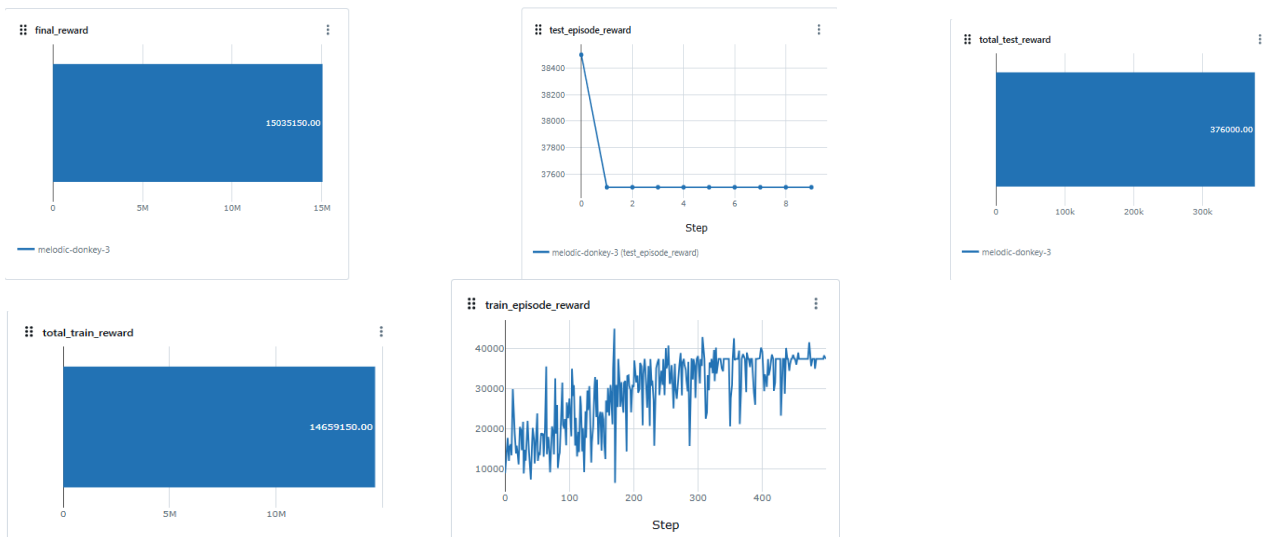
Furthermore, the Q-learning model incorporates both exploration and exploitation techniques. Initially, the model explores different pricing strategies to learn about demand fluctuations and pricing sensitivities. Over time, it begins to exploit the most effective pricing strategies that have yielded higher revenues, thus improving decision-making efficiency. The system is designed to adjust the pricing dynamically, ensuring that the airline can respond to market changes and seat availability throughout the entire sales period.

By using this RL-based approach, the methodology allows the airline to optimize its pricing strategy in a way that maximizes revenue generation while ensuring seat occupancy. It provides a flexible, data-driven solution that adapts to real-time changes in market conditions, offering a competitive edge over static or manually determined pricing

strategies. This dynamic pricing mechanism ultimately enhances the airline's ability to achieve optimal financial performance and meet both revenue and occupancy targets.

IV. EXPERIMENTAL RESULTS

Our proposed demand model, adapted for the airline industry, effectively captured passenger booking behavior across varying lead times using a pre-trained Q-Learning model. Trained over episodes, the model demonstrated its ability to optimize ticket pricing and seat allocation by dynamically responding to changing demand and market conditions. The experimental results revealed that ticket prices generally increased as departure dates approached, reflecting higher demand closer to the departure time. However, a significant price drop was observed in the final lead-time step (from 2 to 1 day before departure) as airlines aimed to fill remaining seats, minimizing wastage. During peak demand periods, such as holidays or high-demand routes, discounts were minimal, aligning with market practices to capitalize on naturally high demand. Conversely, discounts were strategically introduced at the beginning and end of lead times to stimulate demand during low-booking phases, ensuring steady seat occupancy. The model highlighted an inverse relationship between ticket prices and the number of bookings, consistent with market trends, and successfully optimized revenue by balancing early discounted bookings with higher-paying passengers closer to departure. These results align closely with real-world airline revenue management strategies, demonstrating the efficacy of the Q-Learning model in dynamically optimizing pricing and occupancy.



V. CONCLUSION

This study addresses the complexities of flight ticket pricing by proposing a novel sequential game model based on reinforcement learning. The model integrates critical factors such as market demand, enterprise supply, and passenger preferences to develop dynamic pricing strategies. By simulating the decision-making process of intelligent agents, the model identifies optimal pricing strategies for parallel flights, ensuring that airlines can maximize revenue while meeting consumer expectations. Experimental results validate the model's effectiveness, demonstrating its ability to produce rational and stable pricing solutions.

While this research focuses on a two-entity sequential game, future work will expand the framework to accommodate multiple entities, enabling a broader application in competitive markets. This extension aims to further enhance the model's utility in addressing the evolving challenges of airline revenue management and dynamic pricing optimization.

REFERENCES

- [1] Dulac-Arnold, Gabriel, Daniel Mankowitz, and Todd Hester, "Challenges of real-world reinforcement learning," *arXiv:1904.12901* (2019).
- [2] Van Hasselt, Hado, Arthur Guez, and David Silver, "Deep reinforcement learning with double q-learning," *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 30. No. 1. 2016, pp. 2094-2100.

- [3] Lockwood, Owen, and Mei Si, "A review of uncertainty for deep reinforcement learning," *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*. Vol. 18. No. 1. 2022, pp. 155-162.
- [4] Liu Jingxin, Wang Yan, Han Xiao, "Research on edge cloud resource pricing mechanism based on stackelberg game," *Journal of Frontiers of Computer Science and Technology*. 2022, 16(1), pp. 153-162.
- [5] Zhou Xianwei, Gong Qixu, and Yu Songsen, "Computation Offloading Strategy Based on Stackelberg Game and DRL," *Journal of System Simulation*. 2023, 35(2): 372-385.
- [6] Adler Nicole, Amir Brudner, and Stef Proost, "A review of transport market modeling using game-theoretic principles," *European Journal of Operational Research*. 2021, 291(3): 808-829.
- [7] Ding Junpeng, "Research on ticket pricing strategy of Shandong airlines," 2018: 48-60.
- [8] Jiang Binqian, Li Dengfeng, "Two-stage game model of code sharing agreement choosing and tickets' pricing," *Systems Engineering - Theory & Practice*. 2022, 42(3): 724-737.
- [9] Fang Yuan, Le Meilong, "Dynamic pricing of parallel weights based on reinforcement learning," *Journal of East China Jiaotong University*. 2020, 37(1): 47-53.
- [10] Cao, Chenglong, and Xiaoling Zhu, "Pricing Game of Flight Ticket Using Reinforcement Learning," *2024 5th Information Communication Technologies Conference (ICTC)*, IEEE. Hefei, 230601, China. DOI: 10.1109/ICTC61510.2024.10601681.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details