Mini Review
Volume 11:10, 2022

Accounting & Marketing

ISSN: 2168-9601

Open Access

Dynamic Pricing for Parking Solutions

Sarmento Manuela*

Department of New Sciences and Technologies, University of Tehran, Tehran, Iran

Abstract

The need for more effective car park management in public areas like healthcare facilities, shopping malls and office buildings has been brought to light as a result of the rise in the number of automobiles in metropolitan areas. In order to optimize parking utilization and reduce traffic jams, this study combines dynamic pricing with real-time parking data. The practice of adjusting a product's or service's price in response to market trends is known as dynamic pricing. During both off-peak and peak hours, this strategy has the potential to manage vehicle traffic in the parking space. The dynamic pricing method has the ability to set the price of the parking fee to be higher during peak hours and lower during off-peak hours. This paper proposes a technique known as deep reinforcement learning-based dynamic pricing (DRL-DP). On an hourly basis, dynamic pricing is divided into episodes and shifted back and forth. Pricing control is seen as an incentive based on profits and parking utilization rates. In the context of a competitive parking market around the parking area, the simulation output demonstrates that the proposed solution is plausible and efficient.

Keywords: Reinforcement • Automobiles • Parking data

Introduction

The rapid growth of private automobiles is a major issue in many metropolitan areas, particularly in major cities like London, Hong Kong and Kuala Lumpur. The increasing number of automobiles has a negative impact not only on the local population but also on the surrounding environment. The need for parking spaces grows as the number of cars grows. The cars keep going around the area, wasting time looking for a free parking spot. Carbon dioxide emissions and fuel consumption rise as a result, contributing to climate change and the greenhouse effect. The more time a driver spent driving, the more people were stuck in traffic in that area. This sets off a chain reaction that aggrades other drivers and prolongs delays. After realizing the difficulties brought on by the increase in the number of automobiles, numerous academics have attempted to address the issues of traffic congestion and the significant demand for parking lots. Using technologies like sensors (loop or ultrasonic sensor), tickets, or e-payment systems, parking information, such as the availability of free parking spaces, can be received in real time. A chance to create a smart parking system with dynamic pricing is presented by this. By utilizing dynamic pricing, the parking vendor is able to offer price regulation that is adjustable based on a variety of time periods in order to maximize revenue while simultaneously increasing the utilization of parking spaces.To control parking prices based on vehicle volume and occupancy rate, a deep reinforcement learning-based dynamic pricing (DRL-DP) model is proposed in this study.

Description

Reinforcement learning (RL) is recommended for environment modelling because it does not require raw labelled data. Throughout the experiments, RL enables sequential decision-making and provides a complete set of wise choices. In order to lessen traffic congestion and boost parking vendor profits, the dynamic pricing model monitors the various price plans and how they are applied in various contexts. The dynamic pricing model predicts vehicle volume and traffic congestion and distributes vehicle flows. The vehicle flows are distributed to non-peak hours by suppressing drivers' visits to a specific region during peak hours at specific intervals of the day. This increases the rate of parking utilization and reduces traffic jams. This is accomplished by lowering prices and offering incentives like cash back for parking fees. The deep learning agent will gain knowledge from the sequential selection of dynamic pricing in order to enhance the returned incentive in the subsequent episode. Because e-commerce is now a common choice for business models, dynamic pricing has been a pricing technique that has a significant impact on our society. The Internet allows any trade-off, saves many physical costs and has facilitated simple market entrance. Due to the availability of giant data that make user behaviour transparent, many academics are now concentrating on dynamic pricing in e-commerce [1,2].

Four pricing techniques for e-commerce were given by Karpowicz and Szajowski time-based pricing market segmentation and restricted rations dynamic marketing the combined usage of the aforementioned three kinds. On the other hand, Chen and Wang presented a data mining-based dynamic pricing model for e-commerce. The data layer, analytical layer and decision layer were the three bottom-up layers that made up the model. The best pricing strategy for an agent in a multi-agent scenario is influenced by the strategies used by the other suggested a multi-agent reinforcement learning system that incorporates both the opponents' inferential intentions and their observed objective behaviours. A novel continuous time model with price and time-sensitive demand was presented to take into consideration of dynamic pricing usage, order cancellation ratios and various quality of service (QoS) levels in online networks. Reinforcement learning (RL) was suggested as a method by Chinthalapati et al. to examine pricing dynamics in a digital commercial market. The suggested strategy involved two vendors in competition, price and lead time-sensitive customers. They took into account the no-information scenario and the partial information situation as two illustrative examples. In order to establish dynamic pricing on the internet, presented a bargaining agent that made use of a genetic algorithm. Because the mutually agreed deal price is greater than the seller's reserved price but lesser than the buyer's reserved price, online bargaining benefits both the seller and the buyer [3].

The authors in suggested Pareto-efficient and subgame-perfect equilibrium and provided a bounded regret over an infinite horizon. They defined regret as the anticipated cumulative profit loss in comparison to the ideal situation with a known demand model. However, they presupposed that all vendors faced equal marginal costs when considering an oligopoly with dynamic pricing in the face of demand uncertainty. Another research in examined companies' pricing policies in the presence of ambiguous demand. Reference prices and the cost

***Address for Correspondence:** Sarmento Manuela, Department of New Sciences and Technologies, University of Tehran, Tehran, Iran, E-mail: sarmento@222.ac.ir*

Received: 01 October 2022, Manuscript No. Jamk-23-85827; **Editor assigned:** 03 October 2022, PreQC No. P-85827; **Reviewed:** 15 October 2022, QC No. Q-85827; **Revised:** 22 October 2022, Manuscript No. R-85827; **Published:** 29 October 2022, DOI: 10.37421/2168-9601.2022.11.397

of competition, per the study, were the two variables that impacted demand dynamics. Results from simulations showed that companies might reduce the volatility of their pricing path if they collected and analysed customer data and competition since doing so allowed them more control than ever before over uncertainty. In the scenario that supply exceeds demand or vice versa, Wang suggested a dynamic pricing mechanism for the merchant [4,5].

Conclusion

The study determined the best dynamic pricing techniques and stated the equilibrium conditions for those strategies. Compared to the myopic, strategic consumers may have stronger incentive to delay the purchase once they perceive that a significant cost reduction will result in a markdown examined the cost-cutting impact of dynamic pricing on a market with both myopic and strategic customers. Their study showed that consumers tend to delay the purchase when a significant cost-cutting is available, especially for strategic customers. Recently, dynamic pricing research mainly focuses on the financial aspect. Mathematical models are adopted to calculate dynamic pricing based on different game theories applied in different circumstances. Some of the studies have yet to combine dynamic pricing with transdisciplinary research such as artificial intelligence In fact, there is some dynamic pricing research that utilises AI components, but they only focus on e-commerce online platforms such as taoBao and shoppee which analyse user behaviour on their platforms.

Acknowledgement

None.

Conflict of interest

No potential conflict of interest was reported by the authors.

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How to cite this article: Manuela, Sarmento. "Dynamic Pricing for Parking Solutions." J Account Mark 11 (2022): 397.