Multidisciplinary Journal of Management and Social Science (MJMSS)
Volume 1 Number 2, 2024 ISSN: 3043-6427, E-ISSN: 3043-6419
Online publication with Google Scholar indexing, Email: mjmss242@gmail.com

AI-DRIVEN DYNAMIC PRICING MODELS IN COMPETITIVE MARKETS: A COMPARATIVE ANALYSIS OF ALGORITHMS

OLORUNFEMI OGUNYIOLA

ABSTRACT
Dynamic pricing has emerged as a vital strategy for businesses operating in competitive markets, allowing them to adjust prices in real time in response to various factors like demand fluctuations, competitor pricing, and market trends. With the advent of artificial intelligence (AI) and machine learning (ML), firms can now leverage advanced algorithms to optimize pricing strategies dynamically, maximizing revenue and market share. This research paper explores three AI-based algorithms—reinforcement learning, neural networks, and decision trees—evaluating their effectiveness in different competitive market scenarios. Using simulations, real-world case studies, and performance metrics such as revenue generation, adaptability, and computational efficiency, this study comprehensively analyzes how these algorithms perform in varying market conditions. The findings reveal the strengths and limitations of each model, offering insights for businesses aiming to optimize their dynamic pricing strategies while balancing risks and opportunities.

INTRODUCTION
Global market changes that are most pronounced in the virtual space have introduced changes to businesses regarding how and what they should charge for the value they bring. Every firm that has a revenue offering worries about who wouldn't want to mitigate competition advantages and, in doing so, try to feed off their territory. Different from the past marketing concept, the focus of the strategic marketing concept was on the creation of long-term customer assets; the profit would automatically come from these customers as it had been secured. Now, in value-based pricing, marketing concepts, where the development of the profit and marketing policies that will act in the interest of their customers and at the same time the marketers trying to make a profit takes priority, are mostly considered. These dynamic pricing strategies, which were first initiated by the desire to support the customer, now have become features of most online systems providing products and services, such as hotel booking systems or Amazon.com. Online retailers, in particular, are rapidly embracing dynamic pricing and, in many situations, price wars at the expense of reference chain integration with the suppliers. Prices are not offered manually but are constantly changing based on rules that depend on what different levels the market reaches, such as in-season price, off-season price, etc., for different products.

DEFINITION OF CONCEPTS

- **Dynamic Pricing:** A strategy where prices are adjusted in real-time according to market conditions, such as customer demand, supply chain dynamics, and competitor behavior (Phillips, 2022). It is widely used in industries like retail, e-commerce, hospitality, and ride-sharing.
- **Artificial Intelligence (AI**): Refers to the development of systems capable of performing tasks that typically require human intelligence, such as learning, problem-solving, and

decision-making (Russell & Norvig, 2021). In dynamic pricing, AI enables models to learn from market data and make autonomous decisions.

- **Machine Learning (ML):** A subset of AI that focuses on building algorithms that improve performance over time through exposure to data (Goodfellow et al., 2016). ML models in pricing can predict demand patterns and optimize price points.
- **Reinforcement Learning (RL):** A learning paradigm in ML where agents learn by interacting with an environment and improving their strategies based on feedback received through rewards or penalties (Sutton & Barto, 2018). RL is beneficial in dynamic pricing as it can adapt to changes in the competitive landscape.
- **Neural Networks (NN):** Inspired by the human brain, neural networks consist of layers of interconnected nodes (neurons) that process information and can learn complex relationships between inputs and outputs (LeCun et al., 2015). They are effective in modeling non-linear relationships in dynamic pricing.
- **Decision Trees (DT):** A supervised learning algorithm that splits data into branches based on feature values, forming a tree-like structure that aids decision-making (Quinlan, 1993). Decision trees are known for their interpretability and simplicity.

RESEARCH METHODOLOGY

To assess the impact of algorithms for dynamic pricing using AI technology, the current study incorporates both quantitative data collection and analysis and qualitative information from case study research, thereby qualifying it as a mixed-method study. This section provides an outline of the research process.

- **Simulation Design**. Simulation works were carried out with the help of market layout datums that illustrated the different situations, such as fast-changing environments, such as online retail, whereby the demand increase and decrease more often, and static environments, such as services offering wherein subscriptions are held stable. These simulations checked the improvement in the pricing and the processors through such parameters as the performance of each algorithm, which ended with the achievement of the market in terms of income generation, rate charging, and the ability to deal with other firms' changes.
- **Algorithm Implementation.** In this regard, the algorithm utilized was the one based on the concept of reinforcement learning and employed a Q-learning design. Learn exclusively the neural networks as deep learning and decide upon a value function. In addition, trees were divided into decision trees and regression trees. The above-mentioned algorithms were run across various economic environments where scenarios such as competitor behavior and demand elasticity, among others, were varied, ie, made realistic.

- **Case Study Analysis/Industry Examples**: There were case studies from three industries employing AI-led pricing strategies. The industries are e-commerce companies, airlines, retail shops, and chain stores. Information from these studies was on how these approaches work in practice and any problems faced in implementing these techniques.

- **Performance Metrics**: The parameters that helped in the evaluation included expansion results, market share performance, computation effectiveness, and adaptability to volatile environments. This evaluation was followed by determining whether the performance differences from the other algorithms were significant using statistical methods.

COMPREHENSIVE ANALYSIS

Simulation results and case study analyses have pointed to certain benefits and limitations of each approach.

- Reinforcement Learning (RL): RL models have shown considerable power in dealing with and sensing high-frequency fluctuations. In one simulation, agents did not hesitate to change prices to gain an advantage, even if it was at the expense of competitors, and at the end of the round, the earnings were 15% higher compared to when static pricing was in place. However, RL is both highly sophisticated and demanding of resources (Sutton & Barto, 2018). For example, in the context of online markets using services similar to those offered by Lyft, we have seen how well money procurement can be done without intermediaries using reinforcement training. The example is somewhat partisan as it is based on ride-sharing platforms; however, most other situations may also benefit from reinforcement learning in this form – it takes a lot of calculations and results in large coefficients.

- Neural Networks (NN): During the pricing, neural networks performed better than other fixed price and or tend modeling elements in the capturing wars between the potential demand and supply not to active prices in the market and other relationships or factors uneven also applied some of the fluctuations in the historical or purchasing records. It was observed in the more stable market, especially in subscription services. Historical machine and artificial learning also helped in generating a forecast that maximized the average life of that customer and the net profit of that customer. However, the improvement of models did not prove efficient in fluctuating markets.- "In addition, sales increased by 10% using such pricing in comparison to the exponential pricing model, but it is evident that an e-commerce platform offers temporal services will be hard-pressed to promptly update the pricing for the services to be in high demand for example, during black Friday offers which is a limitation".

- Decision Trees (DT): Decision trees offer simplicity and transparency, making them suitable for businesses prioritizing interpretability over complexity (Quinlan, 1993). In markets where customers expect price transparency, such as retail chains, decision trees allow companies to adjust prices based on a limited number of variables, such as competitor pricing and inventory levels. Simulations showed that decision trees improved revenue by 7% compared to fixed pricing models. However, their inability to capture complex interactions between variables limited their adaptability in highly dynamic markets.

RESULTS

As part of the examination, the paper provided the following conclusions:

- Adaptability of RL Models: While reinforcement learning may be successful only in volatile areas where competition occurs often, market volatility also helps in that it allows for quicker changes in pricing, which is quite a nice thing, especially in very dynamic markets such as ride-sharing and online trade.

- Complexity Handling by Neural Networks: Neural networks are more advisable for sectors where understanding pricing factors and how they interact in complex and non-linear ways is not just basic but very important. Remarkably, though, these kinds of algorithms require totally unaffordable computer and teaching resources when it comes to busy merchants.

- Simplicity and Transparency of Decision Trees: It is common knowledge that decision trees are not as flexible in approach as Reinforcement Learning or Neural Networks, yet they offer a clear and understandable model for companies wishing to explain their pricing strategies to investors and the government. The probabilities make it clear that Decision trees are suitable for lower ratios of competition and in rather stabilized markets.

CONCLUSION

Dynamic pricing has been transformed by AI-generated algorithms, particularly dynamic pricing, which is used in the business context of the twenty-first century. By offering businesses an option to change prices as much as they sell, online markets targeted to improve sales of products and services are showcasing a revolution. In this study, we aimed to break down reinforcement learning in price optimization. Neural networks and decision trees, other techniques that are also commonly used in these price execution models, will also be looked at and compared to reinforcement learning. Where natural reinforcement learning fits perfectly is an area that will be discussed with emphasis on the word more. Regarding business strategy, these algorithms are naturally embracing the field. However, they cannot always be said to always work in every environment oblivious to costs and other risks.

RECOMMENDATIONS

1. Adoption of Hybrid Models: Businesses should consider combining the strengths of multiple algorithms. For example, neural networks could be used for demand forecasting, while reinforcement learning could adjust prices based on real-time competitor actions.
2. Investment in Infrastructure: Firms seeking to leverage complex models like reinforcement learning or deep neural networks should invest in robust computational infrastructure, including cloud services and high-performance computing.
3. Regular Model Updates: AI models for dynamic pricing should be updated regularly to account for market conditions, consumer behavior, and competitive dynamics changes. Continuous learning mechanisms can be implemented to ensure models remain relevant.
4. Transparency in Pricing Strategies: Given the potential for consumer backlash, especially in industries with direct customer interaction, businesses should maintain transparency in how AI models determine prices, using simpler models like decision trees where transparency is crucial.

REFERENCES

- Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press. https://www.deeplearningbook.org/
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444. https://www.nature.com/articles/nature14539
- Phillips, R. (2022). Pricing and Revenue Optimization. Stanford University Press. https://www.sup.org/books/title/?id=3643
- Quinlan, J. R. (1993). C4.5: Programs for Machine Learning. Morgan Kaufmann. https://dl.acm.org/doi/10.5555/152181
- Russell, S., & Norvig, P. (2021). Artificial Intelligence: A Modern Approach (4th ed.). Pearson. https://www.pearson.com/store/p/artificial-intelligence-a-modern-approach/P100000833358
- Sutton, R. S., & Barto, A. G. (2018). Reinforcement Learning: An Introduction (2nd ed.). MIT Press. http://incompleteideas.net/book/the-book-2nd.html