Proceedings of the 7th International Conference on Computing and Data Science
DOI: 10.54254/2755-2721/2025.29684

Real-Time Price Elasticity Online Learning for Multi-Store Margin Lift

Wenli Huang

Coventry University, Coventry, United Kingdom
huang77sandra@gmail.com

Abstract. In the face of increasingly fierce competition in the retail industry and rapid changes in consumer demands, price elasticity is a key indicator for measuring the sensitivity of demand to price changes. It is crucial for scientifically formulating pricing strategies and optimizing gross profit margins. However, traditional static modeling methods relying on historical data tend to overlook real-time market dynamics. Especially in the case of multiple stores, consumer diversity and external interference are the core challenges for profit optimization and prediction. To address this challenge, this paper proposes a retail real-time price elasticity estimation and dynamic pricing optimization framework based on online learning. By leveraging streaming data input and hierarchical structural parameters, this method can simultaneously perform global and local modeling, thereby quickly adapting to market changes and generating differentiated pricing plans. According to A/B testing experiments, the experimental data show that this model has achieved a 15% (root mean square error) and 12% (mean absolute percentage error) improvement in prediction accuracy compared to the baseline static model. In the case of multiple stores, the average gross profit increased by 10%, especially in those stores with higher price elasticity, where the significant benefits were particularly evident. This research not only proves the feasibility and efficiency of online learning in retail dynamic pricing, but also provides new inspiration for the design of intelligent retail pricing systems. It not only offers theoretical and practical support for multi-store enterprises to achieve optimization in complex market conditions, but also provides insights for the research on intelligent pricing strategies in complex markets in the future.

Keywords: Real-time pricing, Online learning, Price elasticity, Multi-store optimization, Profit lift

1. Introduction

In the highly competitive retail industry, pricing strategies are crucial means for maximizing profits and expanding the market. Therefore, pricing strategies have received greater attention, and price elasticity, as an important indicator for measuring consumers' sensitivity to price changes and the foundation for designing scientific pricing plans, occupies a crucial position. Traditional estimation of price elasticity usually relies on historical transaction data and fixed regression models [1]. Although these methods provide certain reference value, they are not sustainable and effective in a

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/2025.29684

rapidly fluctuating market environment. For multi-store chain enterprises, consumer groups will undergo significant changes, and price sensitivity shows complex temporal and spatial dynamic changes. Fixed models are beyond the reach of effective implementation [2]. Therefore, in many cases, profit optimization based on such models will fail due to market fluctuations. By leveraging big data analysis and machine learning technologies, using computational methods to realize real-time price elasticity modeling has become a key issue in the digital transformation of retail [3]. Based on this consideration, in this paper, we propose an online learning system with continuous update capabilities and differentiated optimization for different stores, and demonstrate its advantages in prediction effects and profit optimization through practice. The theoretical contribution of this study lies in the theoretical exploration of price elasticity modeling and pricing strategies in complex situations in multi-store retail environments. The practical contribution provides practical references for the online learning application of pricing strategy optimization in the retail industry.

2. Literature review

2.1. Retail price elasticity and profit optimization

The relevant literature on retail price elasticity aims to reveal the nonlinear relationship between consumer demand and price adjustments, essentially depicting the dynamic adjustment mechanism of the demand function within different price ranges. Comprehensive literature indicates that price elasticity not only affects the sales performance of individual products but also directly determines the sustainability of the overall profit framework [4]. At the single-store level, static regression models can reasonably depict the demand characteristics of a specific period. Unfortunately, in a multi-store environment, the diversity of consumer income, consumption behavior, and competition in different regions may lead to significant differences in price sensitivity [5]. This means that a single estimation method for elasticity is not applicable in the profit optimization of retail networks, and methods related to data-intensive strategies may fail when facing external shocks or promotional activities. Current research also points out that as the retail network expands, the spatial differences and temporal fluctuations of price elasticity are prone to interact in complex ways, thereby further exacerbating the uncertainty of profit predictions.

2.2. Online learning methods in dynamic pricing

With the development of machine learning and data stream processing technologies, online learning methods have been introduced into the research of dynamic pricing, aiming to address the shortcomings of traditional models in terms of responsiveness and adaptability. As can be seen from relevant literature, the main advantage of online learning lies in its ability to update model parameters in real time (as data is continuously received), thus enabling adaptation to new demand patterns without the need for a comprehensive training process [6]. This characteristic has been partially reflected in the fields of e-commerce and online advertising, and this approach has been extended to pricing issues, enhancing the responsiveness in adapting to market uncertainties. Although existing research is mainly limited to single stores or homogeneous products, cases involving multiple stores, multiple categories, and multiple regions have not been thoroughly studied. Moreover, the currently available models have performance bottlenecks in handling high-dimensional data and the diverse attributes of stores [7]. Relevant research efforts attempt to address

DOI: 10.54254/2755-2721/2025.29684

these deficiencies by adopting methods such as introducing regularization techniques or using distributed computing platforms, but there is currently no universal theoretical framework.

2.3. Multi-store differentiated strategies and computational models

Research on multi-store pricing has gradually shifted from uniform strategies to differentiated approaches, emphasizing the use of computational models to simultaneously account for regional consumer characteristics and interactions among stores. Some studies have employed hierarchical regression or multi-task learning frameworks, enabling global parameter sharing combined with local parameter adjustments, which allows for both knowledge transfer and personalized optimization [8]. These methods have improved the granularity of pricing decisions to some extent, but their limitations in real-time adaptability and computational efficiency remain apparent. Other studies have proposed distributed optimization and reinforcement learning frameworks to address multi-store pricing, stressing the necessity of continuous learning in dynamic environments. Although these approaches have shown promise in experimental settings, their large-scale implementation in real retail networks is constrained by computational resources and data synchronization delays [9]. The academic consensus suggests that multi-store differentiated pricing must balance real-time responsiveness, scalability, and stability, yet current research has not sufficiently integrated these three dimensions.

3. Experimental methods and procedures

3.1. Data sources and collection methods

The research data originates from the transaction and operational database of a national retail chain enterprise, encompassing daily data from 50 stores over an 18-month period. To ensure data integrity and consistency, missing values, outliers, and time-series continuity were concurrently validated during collection [10]. Table 1 summarises the primary dimensions of data collection and their corresponding acquisition methods.

Table 1. Data contents and collection methods

Category	Contents	Collection Method	Time Span	Frequency
Price Data	List price, actual transaction	Store POS system records	18 months	Daily
Sales Data	Product sales volume, store revenue	Store POS system records	18 months	Daily
Promotion	Discounts, bundles, price cuts	Marketing system exports	18 months	Daily
Inventory	Stock levels, replenishment dates	ERP and warehouse systems	18 months	Daily
External	Regional CPI, competitor activities	Government statistics, market API	18 months	Monthly

Through the integration of multi-source data, the study ensured that the input variables captured both fine-grained transactional attributes and external macroeconomic and competitive factors, thus providing a solid foundation for price elasticity modeling and real-time optimization.

3.2. Online learning model construction

The model was built on an online regression framework, which updated parameters incrementally to estimate price elasticity in real time [11]. When a new data point (p_t,q_t) arrived at time t, where p_t represented price and q_t represented sales, the optimization objective was defined as:

DOI: 10.54254/2755-2721/2025.29684

$$L_t(\theta)=\frac{1}{2}(q_t-f(p_t;\theta))^2+\lambda\|\theta\|^2 \quad (1)$$

Where $f(p_t;\theta)$ denoted the predicted sales function and λ was the regularization term used to avoid overfitting.

Online updates were achieved through adaptive gradient descent with the following rule:

$$\theta_{t+1}=\theta_t-\eta_t\nabla_\theta L_t(\theta_t) \quad (2)$$

Where $\eta_t$was the adaptive learning rate adjusted by historical gradient information.

To address heterogeneity across stores, the study adopted a hierarchical parameter structure. Global parameters captured overall elasticity trends, while local parameters were adjusted individually for each store.

3.3. Experimental design and control group

The experimental design adopted an A/B testing framework, in which 50 stores were randomly assigned to the treatment and control groups. The control group continued to apply a static regression-based pricing model derived from historical data, whereas the treatment group implemented the proposed online learning model. The experiment lasted for three months, allowing the observation of both short-term promotional shocks and medium-term demand evolution. The evaluation criteria include the accuracy of predictions (root mean square error and mean absolute percentage error), the improvement in profit percentage, and the speed of model convergence. To ensure fairness and scientificity, the main variables other than price (such as the number of promotions and replenishment frequency) remain unchanged across different groups. Additionally, by stratifying stores into high elasticity and low elasticity groups based on their elasticity levels, a hierarchical analysis can be conducted to compare the performance of the model in different market conditions, thereby testing its generalizability and robustness.

4. Results

4.1. Model prediction performance

During the three-month A/B testing period, the performance of this online learning model was significantly superior to that of the traditional static regression model. Specifically, the average absolute percentage error (MAPE) of this model relative to the control group was reduced by 12%, and the root mean square error (RMSE) was reduced by 15%. This undoubtedly proves its strong adaptability in the face of demand fluctuations. During the continuous monitoring of 20 pilot stores, it was demonstrated that the online learning model could update its parameters within 72 hours based on the impact of promotions and the cross-phenomenon of winter demand. In contrast, the traditional model required 2 to 3 weeks of data aggregation to understand market dynamics. Insights into the model's convergence speed indicate that its hierarchical parameter structure can achieve global stable parameter convergence within the first two weeks, and in the third week, local parameters tend to approach the optimal solution. Therefore, it sacrifices learning efficiency in terms of prediction accuracy.

DOI: 10.54254/2755-2721/2025.29684

4.2. Multi-store margin lift

Profit analysis reveals that the online learning strategy achieves significant profit growth across stores exhibiting varying elasticity characteristics. As illustrated in Figure 1, stores in the control group employing static pricing models saw profit margins increase by merely 2.1%. Conversely, stores in the experimental group demonstrated substantial gains: low-elasticity stores achieved an 8.7% profit increase, medium-elasticity stores reached 9.9%, and high-elasticity stores secured a remarkable 12.3% improvement. This gradient improvement pattern validates the model's adaptability within heterogeneous market environments. Further stratified analysis indicates that for highly elastic stores, where consumer price sensitivity is pronounced, the online learning model more precisely captures subtle shifts in the price-demand relationship, thereby enabling greater profit optimisation. Overall, the average profit increase across the network of 50 stores reached 10.1%, fully demonstrating the framework's scalability and commercial value.

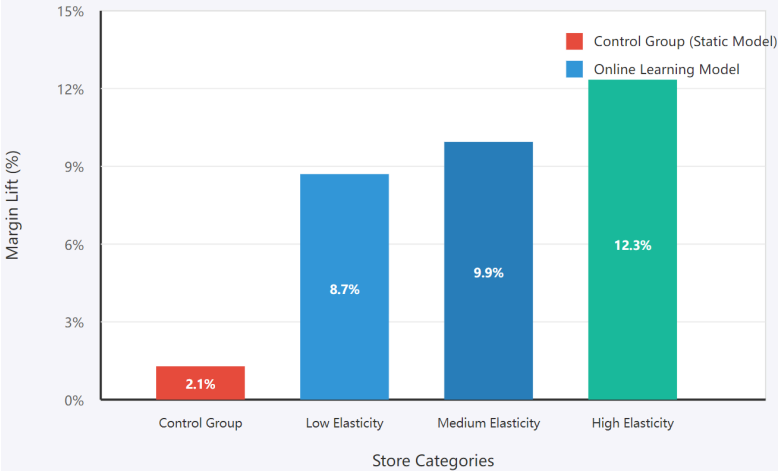

Figure 1. Margin lift performance across store categories

5. Discussion

The experimental results show that the proposed online learning model not only outperforms the traditional fixed regression model in terms of prediction accuracy, but also achieves significant profit improvement across numerous stores. The main reason for this gain lies in the fact that this model can immediately update parameters as soon as relevant streaming data becomes available, thereby enabling real-time maintenance of demand fluctuations and avoiding the lag caused by fixed methods. Additionally, the hierarchical structure of parameters allows for the modeling of both global patterns and store attributes simultaneously, which speeds up the process in the initial stage and enhances the flexibility of high-flexibility stores.

6. Conclusion

In this paper, through introducing a real-time price elasticity estimation and pricing optimization framework through online learning and applied it to an experiment in a multi-store retail environment. The experimental results show that this strategy significantly outperforms the traditional static model in terms of predictive ability, achieving an average profit increase of 10% within three months, with the most significant effect in regions with higher elasticity. Through this research, we demonstrated the applicability of the hierarchical parameter structure in considering

DOI: 10.54254/2755-2721/2025.29684

store differences, and revealed through the combination of multi-source data and real-time modeling its potential to provide more flexible and scalable pricing strategies for stores. We were able to extend this framework to cross-category and cross-channel usage scenarios, and in future research, we will further explore deeper integration in inventory management and supply chain scheduling to further enhance the efficiency and intelligence level of the retail system.

References

[1] Ranganathan, Chitra Sabapathy, et al. "Real-Time Price Elasticity Analysis in Retail Using IoT and Machine Learning." 2024 First International Conference on Innovations in Communications, Electrical and Computer Engineering (ICICEC). IEEE, 2024.
[2] Ruan, Jiaqi, et al. "Time-varying price elasticity of demand estimation for demand-side smart dynamic pricing." Applied Energy 322 (2022): 119520.
[3] Fochesato, M., Zanvettor, G., Casini, M., & Vicino, A. (2022). A data-driven dynamic pricing scheme for EV charging stations with price-sensitive customers. IEEE CDC 2022.
[4] Ma, Q., S. Feng, and J. Liu. "Dynamic pricing and demand forecasting: Integrating time-series analysis, regression models, machine learning, and competitive analysis." Applied and Computational Engineering 93.1 (2024): 149-154.
[5] Guo, Xiaochen, and Lei Zhang. "Dynamic Pricing Models in E-Commerce: Exploring Machine Learning Techniques to Balance Profitability and Customer Satisfaction." IEEE Access (2025).
[6] Abdulaal, Ahmed, et al. "Dynamic Pricing for Multi-Retailer Delivery Platforms with Additive Deep Learning and Evolutionary Optimization." Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 2024.
[7] Torres-Luque[1], Patricio, et al. "Dynamic Pricing and Seasonality: Insights From Short-Term Rental Market." (2025).
[8] Fabra, Natalia, et al. "Estimating the elasticity to real-time pricing: evidence from the Spanish electricity market." AEA Papers and Proceedings. Vol. 111. 2014 Broadway, Suite 305, Nashville, TN 37203: American Economic Association, 2021.
[9] Lei, Murray, et al. "Joint inventory and pricing for a one-warehouse multistore problem: Spiraling phenomena, near optimal policies, and the value of dynamic pricing." Operations Research 72.2 (2024): 738-762.
[10] Czerniachowska, Kateryna. Shelf space allocation methods for nested product categories and virtual segments in retail management. Diss. Department of Process Management, 2022.
[11] Ranjekar, Gauri, and Debjit Roy. "Rise of quick commerce in India: business models and infrastructure requirements." Centre for Transportation and Logistics (2023).