DOI: 10.54254/2754-1169/2026.NJ30743

Multi-Factor Ablation Study in Dynamic Pricing for Electronic Products: Comparing Deep Reinforcement Learning with Traditional Optimization

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Abstract. The dynamic pricing of electronic products is of great significance in the market economy, particularly for revenue optimization in e-commerce. The traditional pricing methods show obvious limitations in the face of the rapidly changing market environment and fluctuations in consumer behavior. This study constructs a systematic dynamic pricing ablation experimental framework, through the accurate deconstruction of the market complexity and quantifies the contribution of four key market factors (price elasticity, brand competitiveness, category popularity, and market randomness) that affect the effect of merchants' pricing strategy. At the same time, At the same time, the research compares the performance of traditional optimization algorithms and reinforcement learning algorithms in different complexity market environments, and uses multiple rounds of repeated experiments, ANOVA significance test and effect quantity analysis to ensure statistical credibility, providing a reproducible experimental paradigm and empirical basis for dynamic pricing related research. The research realizes market "factor decoupling" and verifies the natural advantages of the reinforcement learning algorithm in the face of a highly complex market environment; at the same time, it explains the key role of price elasticity in commodity pricing and provides merchants with scientific pricing and investment strategies for "algorithm-environment matching".

Keywords: Dynamic pricing, Deep reinforcement learning, Market complexity, Price elasticity, Ablation experiment

1. Introduction

Dynamic pricing strategy has become the core element of modern commercial competition, especially in price-sensitive industries such as e-commerce, aviation, and retail. Traditional pricing methods mainly rely on fixed demand assumptions and static models based on historical data, such as linear programming and heuristic optimization algorithms. However, these methods exhibit limited effectiveness in addressing complex market environments, prompting more researchers to turn their attention to reinforcement learning algorithms. Unlike traditional methods, reinforcement learning has strong adaptability and can learn the optimal strategy through continuous interaction

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with the environment. This feature provides the possibility to solve the problem of reliable commodity pricing in a complex and volatile business environment.

The existing literature has conducted multi-dimensional research on the dynamic pricing of commodities. Traditional operations research methods have been used in the field of commodity pricing for a long time. For example, a linear programming model is applied to aviation revenue management, laying the theoretical foundation in the field of dynamic pricing [1]; Researchers have used heuristic algorithms and dynamic programming models based on inventory-competition constraints to dynamically adjust pricing strategies, thereby adapting to market uncertainty [2]. However, these methods have not escaped their fundamental limitations: relying on static models makes it difficult to deal with sudden market changes and changes in consumer behavior. In recent years, the application of reinforcement learning in pricing has made significant progress: The pricing framework based on Q-Learning is explored and applied to retail revenue management [3]; The competition between heterogeneous algorithms can reduce the risk of super competitive pricing. DRL algorithm and traditional TQL algorithm show obvious advantages in competition and collusion [4]; A hybrid method combining fuzzy reasoning and Q-learning is used to deal with uncertainty and assist e-commerce decision-making [5]. Based on the deep Q-learning and actor-critic algorithm model, it can realize the adaptive optimization of different action intervals, and effectively deal with the discrete and continuous differences in the price decision space in the pricing problem [6].

However, two key gaps remain in existing research: First, few studies systematically analyze the specific market factors influencing pricing effectiveness, with most treating the market environment as a “black box”; Secondly, the comparative study of different algorithms mostly focused on the overall performance comparison, and failed to analyze the independent contribution mechanism of each factor deeply. Therefore, based on the actual product price data set, this study aims to answer two core questions in the dynamic pricing research: Which market factors have the greatest impact on the effect of pricing strategy, and which algorithm is the most robust in a complex multi-factor environment? The research constructs a systematic dynamic pricing ablation experimental framework, analyzes the independent contributions of various market factors, evaluates the sensitivity of traditional optimization algorithms and reinforcement learning algorithms in different complexity market environments, and helps managers identify key market factors and adjust investment strategies.

2. Market factor decomposition and data preparation

2.1. Dataset description and feature engineering

This study uses Data Finiti’s electronic product pricing dataset from Kaggle(an open data platform), covering 15,000 products across 10 core fields, including product name, brand, category, price range, and seller. Data include Samsung, Sony, VIZIO,LG, Hisense, and 13 other mainstream electronic product brands; The products cover consumer electronic products such as TV, audio equipment, computers, and accessories. Each category contains multiple system classification labels, such as inventory status, and supports category popularity analysis. The data set can well meet the needs of this study.

Next, this study performs feature engineering. First, perform data quality checks to identify and impute missing values and remove outliers; Subsequently, construct price-related features. Based on the original dataset, this study constructs basic features including mean price, price range, and price ratio. Subsequently, considering the characteristics of the electronic product market, this study

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categorizes products into six price segments: ultra-low(<$50), low($50-150), medium-low($150-400), medium ($400-800), medium-high ($800-1,500), and high (>$1,500).

2.2. Independent modeling of core market factors

First, base elasticity (base_elasticity) is category-specific, ranging from -1.5 to -0.3: necessities (e.g., laptops) are assigned -0.5, entertainment devices (e.g., audio equipment) -0.7, and accessories -1.5 (see Equation (1)). In addition, this study further introduces three adjustment layers: brand positioning adjustment accounts for the lower price sensitivity of customers of premium brands (e.g., Apple), price tier adjustment is based on the price-quality signaling effect for high-priced goods [7], and necessity adjustment captures functional dependency differences across product categories. After adjustment, the elasticity range is [-1.62, -0.13].

$$\text{Price elasticity} = \text{base\_elasticity}*\text{brand\_modifier}*\text{price\_modifier}*\text{necessity\_modifier} \tag{1}$$

Second, brand competitiveness. Following brand positioning theory [8], this study assigns competitiveness scores to nine brands in the dataset: premium brand Apple receives 0.95, high-end brands (Sony, Samsung, Bose) receive 0.80-0.90, mid-tier brands (ASUS, LG, Logitech) receive 0.60-0.75, and budget brands (TCL, Hisense) receive 0.30-0.50. These scores integrate brand reputation, perceived quality, and customer loyalty; high-end brands with strong brand equity command greater pricing power and lower demand elasticity [9].

Third, category popularity. The characteristics of product categories significantly influence consumer demand, with different categories exhibiting varying levels of attractiveness to consumers [10]. This study establishes the benchmark score of each electronic product category and integrates the characteristics of product categories through the weighted average mechanism. By differentiating weight settings, the approach reflects consumer attention to different product dimensions. For instance, core categories such as the weight of core categories such as smartphones and computers is 1, the weight of important categories such as audio devices and headphones is 0.8, and the weight of standard categories is 0.6.

Fourth, market randomness. To simulate a real and dynamically changing market environment, the market randomness factor is introduced by setting intervals for factors that may cause market fluctuations, such as market trends, seasonal factors, competitive pressure, and random noise. This factor serves as a moderating element in the demand function, enabling the same product to generate demand fluctuations of 10-30% in different time steps [11]. The design ensures that the simulation environment has dynamic characteristics of three scales at the same time: long-term trend, periodic fluctuation, and random impact.

3. Model configuration and training

The study formulates a unified demand function based on baseline demand and the four core market factors (see Equation (2)). The elasticity component is calculated on the basis of benchmark demand level 1, superimposing the product of price elasticity and relative price change rate, and setting a lower bound constraint of 0.1 to ensure that 10% of core customer demand is still retained in the case of extremely high prices. The relative price change rate is defined as the difference between the current price and the benchmark price divided by the benchmark price. The demand function also includes an extreme pricing penalty (extreme_penalty): it imposes a 70% demand reduction (i.e., 30% retention) for prices between 1.5× and 2.0× the benchmark, and a 90% reduction (10%

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retention) for prices exceeding 2.0×, ensuring that the algorithm exploration is within the reasonable pricing space.

$$D(p) = Base\_Demand \times Elasticity\_Component \times Brand\_Component$$

$$\times Category\_Component \times Market\_Component \times Extreme\_Penalty \tag{2}$$

For the profit function, due to the lack of real cost data, the experiment assumes that the cost rate is within the range of 65% -75% of the price according to the industry average level, and verifies the robustness of the conclusion through sensitivity analysis. The cost of electronic products determined in actual production is relatively fixed and generally does not fluctuate significantly with the fluctuation of their pricing. Therefore, fixed costs are used for estimation and applied to the definition of the profit function. See Equation (3):

$$\mathrm{Profit(p)} = \mathrm{p} \times \mathrm{D(p)} - \mathrm{unit\_cost} \times \mathrm{D(p)} \tag{3}$$

For the ablation experiment control mechanism, six configurations are designed via independent on/off control of each factor to measure the marginal contribution of individual factors: Full_Model, No_Elasticity, No_Brand, No_Category, No_Randomness, and Minimal_Model. These six configurations form a market complexity gradient from simple to complex, where market complexity is defined as the number of independent factors affecting pricing decisions and the intensity of their nonlinear interactions. Six configurations form a market complexity gradient from simple to complex: the Minimal_Model contains only the price elasticity factor, and the market complexity is the lowest; The Full_Model contains all four factors and their possible interaction effects, and the market complexity is the highest; The other four configurations remove a factor respectively, forming a market environment of medium complexity. At the same time, market complexity is defined as a comprehensive measure of the number of independent factors that affect pricing decisions and their nonlinear interaction strength. The higher the complexity of the environment, the larger the state space dimension that the algorithm needs to deal with, and the higher the difficulty of strategy optimization. For each configuration setting, 5 rounds of repeated experiments, 500000 training steps, and 200 evaluation rounds were conducted to observe the law of algorithm performance changing with market complexity and ensure the significance of statistical results.

Regarding the reinforcement learning algorithm architecture, the study formulates the dynamic pricing problem as a Markov Decision Process (MDP) defined by the tuple ⟨S, A, P, R, γ⟩, where:

• State space $S \in \mathbb{R}^{10}$: A 10-dimensional vector encoding product index, price elasticity, brand competitiveness, category popularity, and market randomness factors

• Action space A: 21 discrete price multipliers {0.5, 0.6, ..., 2.4, 2.5}

• Reward function R: A composite function R(s,a) = profit/1000 + demand_bonus - extreme_penalty

• Discount factor γ: Set to 0.95 for temporal credit assignment

The agent learns a policy π: S → A that maximizes the expected cumulative reward through interaction with the pricing environment. The system implements DQN and PPO with optimized hyperparameters: DQN employs a lower learning rate, a large replay buffer, and extended exploration; PPO uses a moderate learning rate, larger batches, and policy clipping. The two reinforcement learning algorithms were compared with the traditional optimization in six ablation

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configurations through multiple repetitions, and the statistical reliability was verified by variance and effect size test.

4. Experimental results and analysis

The complete experimental results based on the six ablation configurations are shown in Table 1. Based on overall average profit, PPO achieves the highest average profit ($446,863), followed by DQN ($426,176); the traditional optimization algorithm serves as the benchmark with an average profit of $369,986. Compared with the traditional optimization algorithm, PPO and DQN achieved 20.8% and 15.2% performance improvement, respectively, which verified the advantages of the reinforcement learning algorithm in dynamic pricing. By quantifying the "average performance/standard deviation" index and comprehensively considering the performance level and fluctuation degree, the robustness score of the algorithm is obtained. Among them, DQN is the most robust (7.8 points) and shows good environmental adaptability under different market complexity configurations; PPO takes the second place (7.5 points). Although the average performance is better, it fluctuates greatly in some complex configurations. The traditional algorithm is the worst (6.8 points), which proves that its performance has a significant downward trend in the face of a complex market environment.

Table 1. Comparison of core experimental results

Index	Traditional	DQN	PPO
Index overall average profit	$369,986	$426,176	$446,863
standard deviation	$55,801	$56,377	$61,125
Cohen's	--	1.002	1.314
Robustness score	6.8	7.8	7.5
Performance ranking	3rd	2nd	1st
Improvement over Traditional	benchmark	+15.2%	+20.8%

As illustrated in Figure 1, the heatmap illustrates the nonlinear relationship between algorithm performance and market complexity. In the Full Model configuration, PPO performs best in dark red, and removing any factor will lead to performance degradation. The traditional optimization algorithm shows significant performance fluctuations under moderate complexity environments, especially experiencing a profit valley in the No_Randomness configuration, while PPO and DQN maintain a relatively stable upward trend with the increase of complexity, validating the robustness advantage of reinforcement learning algorithms in dealing with multi-factor coupled environments.

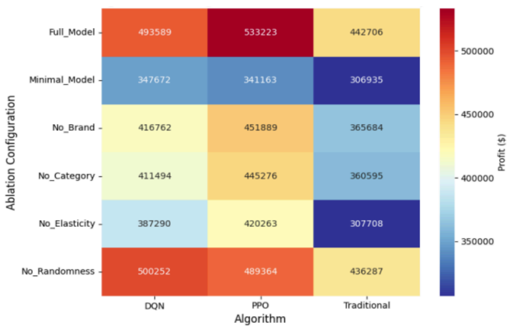

Figure 1. Algorithm-configuration performance heatmap

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Figure 2 shows the dynamic curves of the three algorithms in the face of changes in market complexity. PPO was the highest and gradually increased; The traditional algorithm shows obvious U-shaped fluctuation, and rebounds after no random drop to the lowest point; DQN remained at a median level and relatively flat. At the same time, it can be seen that the starting points of the three algorithms in the minimum_model are similar, and they differentiate rapidly with the increase of complexity, revealing that reinforcement learning algorithms can effectively use multi-factor information, while traditional algorithms are more sensitive to the combination of complex factors.

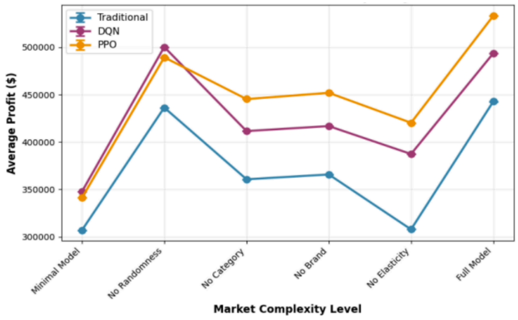

Figure 2. Algorithm performance under different market complexities

The importance of each market factor is quantified via ablation experiments: the price elasticity factor has the highest relative importance (24.1%), followed by category popularity (17.2%) and brand competitiveness (16.0%). Removing this factor will lead to a decrease in profits of $118086; Category popularity (17.2%) and brand competitiveness (16.0%) followed, resulting in $84051 and $78395 performance losses, respectively. The contribution of the market randomness factor was the lowest (3.0%), which only affected the profit change of $14538. The key driving factors of dynamic pricing of the electronic product dataset are: Price Elasticity > Category Popularity > Brand Competitiveness > Market Randomness.

As illustrated in Figure 3, the four factors evolve independently in the time series, successfully realizing the accurate deconstruction of market complexity. The price elasticity factor fluctuates greatly in the negative value area (-0.8 to -1.5), and the fluctuation range is significantly higher than other factors. This high volatility explains the price elasticity factor's dominant contribution of 24.1%—not only does its negative characteristic clarify the economic principle of price reduction stimulating demand, but further requires that the pricing algorithm has strong adaptability and can capture the differential elasticity levels of different products and market states. In contrast, category popularity shows periodic oscillation characteristics, reflecting the natural laws of product life cycles; brand competitiveness and market randomness factors remain relatively stable (the fluctuation amplitude is less than ±0.2), indicating that their operational mechanisms have the characteristics of sustainability rather than dramatic changes. This temporal analysis verifies the effectiveness of independent four-factor modeling and reveals the internal relationship between factor volatility characteristics and importance contributions. In this study, a systematic statistical significance test was conducted to verify the reliability of the differences between the algorithms. ANOVA results showed that the differences among the three algorithms were highly significant (f=8.52, p<0.0001). The effects of PPO and DQN were 1.314 and 1.002 (both large effects) compared with the traditional algorithm, which proved the statistical reliability of the reinforcement learning algorithm.

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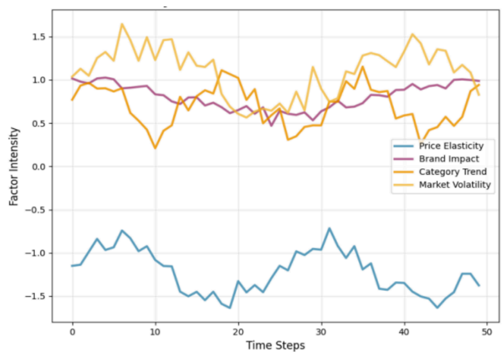

Figure 3. Dynamic market factors over time

5. Conclusion

By designing a systematic dynamic pricing experimental framework, this study attempts to answer two questions raised in the introduction: the contribution of four market factors and the performance comparison of the algorithm in a complex multi-factor environment. The experimental results confirm the advantages of reinforcement learning algorithms (DQN, PPO) in complex dynamic pricing scenarios and establish a "algorithm-environment matching" decision-making framework. PPO performs best in high complexity environments (the performance of full_model is improved by 56.3%), and DQN is the most robust (the robustness score is 7.8). Traditional optimization is suitable for simple scenarios. The ablation experiment design deconstructs the complexity of the market, avoids the problem of fuzzy contribution caused by cross contamination of factors in previous studies, and accurately quantifies the independent contribution of four factors: price elasticity>category popularity>brand competitiveness>market randomness, which fills the problem that the existing research regards the market environment as a "black box" and lacks factor level attribution analysis, and provides resource investment suggestions for businesses. Taking the electronic product data set used in this experiment as an example, businesses should give priority to investing resources to obtain price elasticity data, and then optimize category popularity and brand competitiveness, and appropriately reduce the resource investment of market randomness. At the same time, this research framework has good scalability and can be used as a reference for other researchers to carry out similar ablation research in the pricing services of hotel reservation, shared travel, and other fields.

However, the current study has limitations: market randomness factor modeling is simplified (failing to capture nonlinear events such as promotions and competitive strategy mutations), the fixed cost assumption overlooks dynamic structures, and only single-product pricing is addressed. Future research should introduce Markov Jump Processes or Generative Adversarial Networks to simulate market mutations, integrate multimodal data sources (social media trends, sentiment analysis of user reviews, etc.), and establish industry-specific factor libraries to enhance system practicality and decision targeting.

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