A Review of Optimal Replenishment and Pricing Strategies for Fresh Vegetables

Qianrong Zhang [1,2], Hazirah Bee Yusof Ali [1*]

[1] Faculty of Information Technology, City University Malaysia, Darul Ehsan, 46800, Malaysia
[2] College of Big Data and Artificial Intelligence, Chengdu Technological University, Chengdu, 610000, China
* Correspondence: Hazirah Bee Yusof Ali

Abstract: Fresh vegetables, as typical perishable products, present significant challenges in supply chain management due to their inherent perishability and high price sensitivity. This paper systematically reviews the recent research progress in optimal replenishment and pricing strategies for fresh vegetables. Firstly, the study explores pricing models based on cost-plus mechanisms and price elasticity, analyzing how retailers utilize economic indicators to refine demand forecasting and balance profit margins against spoilage losses. Secondly, it reviews replenishment decisions considering deterioration rates and preservation technology investment (PTI), with a particular focus on the mitigating effects of PTI on non-instantaneous deterioration and the impact of stochastic risks such as customer returns on inventory stability. Finally, the review summarizes systematic planning and multi-objective optimization methods under operational constraints, highlighting the application of machine learning algorithms and swarm intelligence in enhancing supermarket revenue and customer satisfaction. This review not only provides a methodological framework for intelligent decision-making in fresh food retail but also identifies key directions for constructing resilient fresh supply chains in uncertain environments.

Keywords: fresh vegetables; joint replenishment and pricing; price elasticity of demand; preservation technology; multi-objective optimization

1. Introduction

Fresh vegetables represent a typical category of perishable produce, characterized by significant demand volatility, short shelf lives, high spoilage rates, and intense price sensitivity. These traits render their supply chain management far more complex than that of durable goods. At the retail level, excessive replenishment lead to surging costs associated with decay and disposal, whereas insufficient replenishment results in stockout losses and customer attrition. Furthermore, as a core factor influencing consumer demand, pricing is highly coupled with replenishment decisions, forming a typical Joint Replenishment and Pricing Problem (JRPP).

In recent years, against the backdrop of "New Retail," community group buying, and smart agriculture, the enhanced capability for data acquisition has shifted research focus from traditional inventory models toward data-driven approaches and intelligent optimization. Consequently, a systematic review of the research progress regarding replenishment and pricing strategies for fresh vegetables is of profound significance for both theoretical depth and practical application. This review is structured around the following dimensions:

(1). Modeling methods for traditional replenishment and pricing strategies.

(2). Applications of machine learning methods in this field.

(3). Research progress in multi-objective optimization models.

(4). Future research trends and prospects.

2. Research Methods of Replenishment and Pricing Strategies

2.1 Pricing Models Based on Cost-plus and Price Elasticity

Fresh vegetable commodities possess extreme temporal sensitivity and perishability, characterized by market values that decay rapidly as freshness diminishes. In retail practice, pricing serves not only as a mechanism for profit acquisition but also as a critical variable for regulating inventory loss and driving replenishment cycles. A systematic review of existing literature reveals that fresh produce pricing has transitioned from traditional cost-driven paradigms toward dynamic models integrated with a multidimensional "cost-market-behavior" framework.

Huang [1] posits that the fundamental pricing archetype utilized in supermarket operations is the cost-plus pricing method. The primary intent of this approach is to ensure that gross sales revenue fully covers procurement costs while securing a stable net profit. However, the biological uniqueness of vegetables dictates that "shrinkage loss" must be treated as a significant implicit cost. Chen et al.[2] deepened this logic by proposing that supermarkets must incorporate the historical average loss rate of specific categories as a key denominator in the pricing formula. This adjustment ensures value compensation for "disappearing assets" caused by physical decay. The mathematical model for cost-plus pricing is formulated as follows:

$$m_i = (1 + w_i) \times \frac{p_i}{1 - e_i} \tag{1}$$

Where, m_i represents the automated pricing result for the i-th vegetable item; w_i denotes the preset profit markup rate, the magnitude of which is typically dictated by the retailer's strategic positioning; p_i is the real-time wholesale cost; and e_i represents the average daily loss rate for that category.

Research by Chen et al. demonstrates that while this model protects the financial baseline, its static nature proves insufficient in highly competitive market environments. Relying solely on wholesale price fluctuations to adjust retail prices often neglects the consumer's psychological threshold for price changes, which can inadvertently lead to inventory accumulation or the sacrifice of potential gross margins.

To mitigate the passivity of cost-plus pricing, scholars have introduced the theory of Price Elasticity of Demand (PED) from microeconomics. Zhu [3], in discussing asset pricing under uncertainty, emphasizes that the behavioral choices of decision-makers are deeply dependent on their assessment of market ambiguity. In vegetable retail, this uncertainty manifests as non-linear feedback between price and sales volume. Nie et al. [4] argued that demand for fresh products reacts with significant variance to price changes across different categories. By constructing a double-log demand function, they effectively quantified this sensitivity to provide a robust foundation for pricing corrections. The estimation and correction model for price elasticity of demand is as follows:

$$\ln(Q_{it}) = \alpha_i + \beta_i \ln(P_{it}) + \sum \gamma_{ij} \ln(P_{jt}) + \epsilon_{it} \tag{2}$$

Where Q_{it} represents the actual sales volume of item i during period t; P_{it} represents its specific sales price; β_i is the coefficient of price elasticity of demand; and γ_{ij} is the cross-price elasticity, reflecting the substitution or complementary effects between items within the same category.Figure 1 is a schematic diagram of the demand price model.

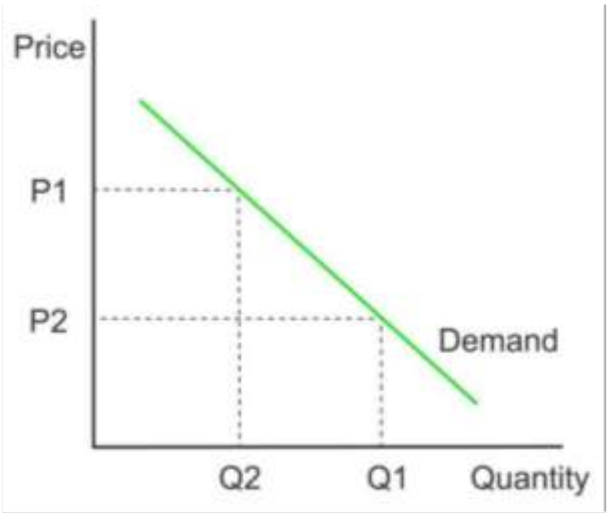

Figure 1. Demand price model

Most leafy vegetables are high-elasticity goods ($|\beta_i| > 1$), meaning minor price adjustments can trigger substantial fluctuations in sales volume. Consequently, researchers established a price elasticity correction function to dynamically adjust initial sales forecasts. This integration of economic theory with predictive modeling ensures that pricing strategies possess both a cost-compensation function and a proactive capability to regulate demand and optimize replenishment. Managing hundreds of vegetable items presents a significant challenge in selecting the optimal sales mix and matching it with precise pricing strategies. Huang suggested that pricing decisions should not be made in isolation but should consider the synergistic effects within category groups.

To address this complexity, introduced the Entropy Weight Method combined with the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) model. This method processes indicators such as historical sales volume, daily revenue, profit margins, and loss rates through dimensionless normalization. By objectively determining weights via the entropy method, all available items are ranked based on their contribution. Under this multi-criteria decision-making framework, pricing is determined not just by wholesale costs but by the overall "contribution score" of the item. Results indicate that high-scoring items identified through this multi-dimensional system exhibit significantly higher gross profit levels when elastic pricing is applied compared to simple cost-plus pricing. Furthermore, the "uncertainty aversion" behavior noted by Zhu is evident in supermarket pricing; We concluded that retailers mitigate supply chain volatility by using price elasticity as a lever, transforming uncertain loss risks into controllable sales adjustments. In summary, research on fresh vegetable pricing has matured into a system consisting of a cost-plus foundation, price elasticity as the dynamic core, and multi-indicator evaluation as the screening criterion. This systematic methodological chain provides a precise demand baseline for subsequent replenishment volume decisions in complex environments.

2.2 Replenishment Decisions Considering Deterioration Loss and Preservation Investment

Fresh vegetable replenishment is fundamentally distinct from non-perishable inventory management due to the continuous physical decay of the goods. In the existing literature, replenishment strategies have evolved from basic economic order quantity models to complex systems that account for time-varying deterioration rates and the strategic impact of preservation investments. Huang [5] established the theoretical groundwork by emphasizing that the inventory level of fresh produce does not merely decline linearly due to sales but follows a non-linear trajectory driven by natural decay. This decay is often modeled using a deterioration rate function, commonly represented by a Weibull distribution or a constant coefficient, which reflects the increasing probability of spoilage as the product ages. Chen [6] further explored this by analyzing retailer behavior in the context of dual-channel supply chains, noting that replenishment logic must shift significantly between the "fresh stage" and the "decay stage" of a product's life cycle.

When vegetables enter the decay stage, the marginal loss of holding inventory begins to outweigh the marginal gain from potential sales, necessitating a "just-in-time" replenishment approach to minimize waste. The basic differential equation describing the inventory status $I(t)$ at any given time t is expressed as follows:

$$\frac{dI(t)}{dt} + \theta(t)I(t) = -D(p,t) \tag{3}$$

In this model, $\theta(t)$ represents the time-varying deterioration rate, and $D(p,t)$ is the demand function sensitive to both price and time. A critical advancement in this field is the transition from treating deterioration as an uncontrollable exogenous variable to an endogenous factor that can be mitigated through technology. Cui et al. [7] introduced the concept of "non-instantaneous deterioration," arguing that retailers can extend the initial period of zero-decay through preservation technology investment (PTI). By investing in cold-chain logistics or modified atmosphere packaging, retailers can effectively create a "buffer period" during which the vegetable maintains its peak quality. This investment is modeled by an effort level variable f, which determines the extension of the non-decay duration t_d. The correlation between investment and the preservation effect is often defined by a logarithmic function:

$$t_d(f) = t_0 + \eta \ln(1 + f) \tag{4}$$

Where η represents the efficiency of the preservation technology. He demonstrated that an optimal replenishment cycle is achieved when the cost of preservation investment is balanced against the reduction in spoilage-related revenue loss.

Table 1. Comparative analysis of replenishment decision methods

Research Perspective	Representative Literature	Method of Handling Deterioration	Core Decision Objective
Life Cycle	Huang (2008)	Weibull distribution describing the deterioration rate	Total revenue over dynamic life cycle stages
Technical Investment	Cui et al. (2023)	Non-instantaneous deterioration period model	Balance between preservation investment and loss reduction
Channel Behavior	Chen (2023)	Inventory functions based on supplier behavior	Inventory optimization under cross-channel competition
Reverse Logistics	Zhao & Liu (2022)	Stochastic probability distribution of returns	Minimization of fixed costs and return-related losses

Beyond physical decay, the replenishment process is further complicated by stochastic risks, particularly consumer return behaviors. Zhao and Liu [8] addressed this by incorporating customer returns and fixed ordering costs into a joint replenishment-pricing model. In the e-commerce and high-end fresh food sectors, liberal return policies can lead to significant inventory volatility, especially since returned vegetables often cannot be resold due to hygiene or quality degradation. It make we to utilized stochastic dynamic programming to prove that the optimal replenishment policy follows an (s, S, p) structure. Under this strategy, a replenishment order is triggered only when the inventory level falls below a critical threshold s, bringing the stock up to an optimal level S. Their findings suggest that when the return rate or fixed ordering costs are high, retailers should adopt a more conservative replenishment stance, prioritizing high-frequency, small-volume orders to hedge against the risk of excessive unsalable stock. This approach ensures that the replenishment cycle remains resilient to the "reverse logistics" shocks that are common in modern retail, as described in table 1.

In summary, the synthesis of these research methods demonstrates that modern vegetable replenishment is no longer a localized task of stock counting. Instead, it is a sophisticated coordination process that integrates the biological laws of decay, the economic trade-offs of preservation technology, and the management of stochastic consumer risks. By shifting from a static "cost-plus" baseline to a dynamic "deterioration-aware" model, retailers can significantly reduce the physical waste of produce while maintaining high service levels. This evolution in replenishment methodology provides the necessary operational framework to support the high-frequency turnover requirements of the fresh food industry, ultimately bridging the gap between theoretical inventory optimization and practical supply chain resilience.

2.3 Systematic Planning and Multi-objective Optimization under Multi-constraints

In the practical operational environment of fresh food supermarkets, replenishment and pricing decisions are rarely made in a vacuum; rather, they are subject to a complex array of operational constraints including limited shelf space, budget allocations, and the inherent correlation between different vegetable categories. Wang and Zhou [9] argue that the transition from individual item management to systematic category planning is essential for maximizing overall commercial returns. By employing linear programming models, researchers have successfully integrated daily sales data with wholesale costs to construct objective functions aimed at revenue maximization. The complexity of these models arises from the need to balance the "demand fulfillment rate" against the "risk of overstocking." he utilized time-series forecasting and fuzzy comprehensive evaluation to determine specific daily replenishment volumes, ensuring that the supply of high-demand items like broccoli or chili peppers is prioritized during peak periods. This systematic approach allows retailers to move beyond reactive restocking toward a predictive model that aligns inventory levels with anticipated market fluctuations. The general objective function for such a revenue maximization model is defined as:

$$\max Z = \sum_{j=1}^{T} \sum_{i=1}^{n} [m_{i,j} \cdot \min(h_{i,j}, D_{i,j}) - p_{i,j} \cdot h_{i,j}] \quad (5)$$

In this equation, $m_{i,j}$ and $h_{i,j}$ represent the selling price and replenishment volume of item i on day j, respectively, while $D_{i,j}$ represents the forecasted demand.

However, a single-objective focus on revenue often ignores the strategic importance of market share and customer satisfaction. To address this, Deng et al. [10] developed an intelligent replenishment and pricing model specifically for perishable products, utilizing Back Propagation (BP) neural networks to fit the non-linear relationship between total sales volume and cost-plus pricing. Their research highlights that the distribution of vegetable sales follows significant seasonal and temporal patterns, which necessitates a multi-objective optimization framework. By leveraging Particle Swarm Optimization (PSO) and Long Short-Term Memory (LSTM) networks, They demonstrated that optimizing replenishment quantities can lead to a profit increase of over 90% compared to traditional empirical methods. This suggests that systematic planning must account for the "joint elasticity" of various items, where the pricing of one product can significantly influence the sales of another related category.

The integration of correlation analysis, such as the Pearson and Spearman correlation coefficients used by Deng et al.and Wang and Zhou, further refines the systematic decision-making process. These analyses reveal that certain vegetable categories (e.g., peppers and cauliflowers) exhibit strong positive sales correlations, suggesting that they should be replenished and priced as a coordinated unit rather than isolated products. Zhao and Liu added another layer of complexity to this systematic view by introducing the constraints of "fixed ordering costs" and "stochastic return rates." Their work emphasizes that in a multi-period planning horizon, the cumulative effect of small-scale losses can be mitigated by an (s, S, p) policy that accounts for the fixed costs associated with each replenishment event. When these logistical costs are high, the optimal strategy shifts toward fewer, larger-scale replenishment cycles, provided that the deterioration risk is managed through the technologies discussed in previous sections. This highlights the interdependency between logistical constraints and pricing flexibility, where the cost of order fulfillment sets a lower bound for sustainable pricing strategies.

Finally, the use of advanced evaluative frameworks like the Entropy-TOPSIS model, as emphasized by Chen et al, provides the final piece of the systematic planning puzzle. By assigning weights to multiple indicators —such as demand satisfaction, gross profit, and shelf-life —retailers can perform multi-criteria sorting to determine which items should be prioritized in the limited display space of a supermarket. This multi-objective optimization approach, often solved using algorithms like NSGA-II to find the Pareto-optimal front, allows decision-makers to select a strategy that balances the inherent trade-off between maximizing immediate revenue and ensuring long-term customer loyalty through high demand-fulfillment rates. In conclusion, the current state of research suggests that the most effective replenishment and pricing strategies are those that treat the supermarket's vegetable section as a unified ecosystem, where mathematical programming and machine learning converge to solve high-dimensional optimization problems under real-world constraints. This holistic perspective ensures that the final replenishment plan is both financially lucrative and operationally feasible within the constraints of modern supply chain management.

3. Conclusion and Prospects

3.1 Conclusion

This paper provides a comprehensive review of replenishment and pricing strategies for fresh vegetables. Existing research has evolved from simple cost-driven models into sophisticated integrated decision systems that combine cost-plus pricing, price elasticity corrections, and multi-objective optimization. Evidence suggests that investing in preservation technology can significantly delay deterioration, while integrating deep learning methods (such as BP neural networks and LSTM) with optimization algorithms (such as NSGA-II and PSO) effectively addresses non-linear demand forecasting and cross-category correlation effects. These advancements significantly improve operational efficiency for retailers, achieving a scientific balance between satisfying market demand and maximizing enterprise profitability.

3.2 Future Research Directions

Despite the substantial progress in current research, several areas warrant further exploration. Future research should prioritize the following three dimensions: First, Omni-channel Supply Chain Integration, exploring coordinated inventory sharing and differentiated pricing strategies in the context of merging online and offline retail. Second, Precise Characterization of Uncertainty, investigating the impact mechanisms of extreme weather and supply chain disruptions on vegetable spoilage and demand volatility. Third, Sustainability and Social Responsibility, incorporating the social costs of carbon emissions and food waste into decision models to foster a green, low-loss, and environmentally sustainable modern fresh retail ecosystem.

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