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# Optimizing Perishable Supply Chains Under Stochastic Demand: Dynamic Pricing Versus Fixed Discount Strategies

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**ABSTRACT**

Post-harvest losses (PHL) in Bangladesh's tomato supply chain result in significant food waste, economic loss, and supply chain inefficiencies due to high perishability and unpredictable demand. Using mathematical modeling and Monte Carlo simulation, the research compares fixed discount and dynamic pricing strategies. Results show that dynamic pricing, especially with strong demand boost factors, improves profit by up to 8.48% even as quality declines. This research contributes to the field of agri-supply chain optimization by presenting an adaptable framework for decision-making in volatile and resource constrained environments. The findings offer actionable insights for farmers, retailers, and policymakers seeking to build more resilient, efficient, and sustainable perishable supply chains in Bangladesh and similar contexts.

Keywords: Supply chain network, perishable good, stochastic demand, Monte Carlo Simulation



## 1. Introduction

Agriculture plays an important role in Bangladesh's economy, contributing to 11.22% to Bangladesh GDP[1]. Among perishable agricultural products, tomatoes are a vital crop due to their high demand and nutritional value. Farm level postharvest loss of tomato was 12.45% per farm in the survey area. From this 3.59% was due to partial damages and the rest 8.86% was for full damages of tomato[2].Primary causes of post-harvest losses in tomatoes include insect, pest, and disease attacks, lack of cold storage facilities, inadequate processing industries, insufficient investment capital, poor market information flow, and inadequate packaging materials[3]. Postharvest losses can be minimized through better storage, farmer training, and improved market access[4]. In supply chain management, multi-echelon strategies enhance customer satisfaction by ensuring timely deliveries and meeting both soft and hard time window requirements[5]. Stochastic demand refers to the unpredictable and random nature of customer demand for products or services[6]. It is directly affects inventory decisions, particularly in continuity involving substitute products[7].Tomato demand in Bangladesh is uncertain due to seasonal shifts, price changes, and consumer preferences[8]. Stochastic demand models address this variability, supporting better inventory management and resource allocation[9]. As a result, the distribution network must be carefully planned for post harvest supply action. In this article, a supply chain model for perishable networks was created, taking into account the stochastic character of consumer demand.

## 2. Literature Review

A perishable goods supply chain survey came under public criticism. Customers with more health conscious require more and more high quality for perishable products at a fair price [10]. In a supply chain network, competition among businesses leads to stringent cost, quality, and timing controls for perishable goods [11]. The structure of the supply chain infrastructure for perishable goods is becoming more complicated and is connected to the superposition of numerous network types [12]. The supply chain for perishable goods is distinct from other models and is thought to be crucial for things like food safety and quality [13]. Food security is increased and post-harvest losses are decreased with effective supply chain management. Multi-echelon systems, product shelf life, and uncertain demand have all been taken into account in earlier research. Post-harvest losses from pests, illnesses, and spoiling are made worse by climate change. According to studies, in Sub-Saharan Africa, up to 37% of food is lost throughout the harvest, storage, and marketing processes. These observations reinforce the study's focus on Bangladesh's tomato supply chain by highlighting the need for improved supply chain strategies [14]. Poor handling, inadequate cold chain systems, and low farmer awareness drive losses, while improved storage, transport, and low cost method can enhance food security [15]. A great review of perishable products and inventory management was given by Nahmias [16]. Belien and Force examined blood product supply chain management and inventory [17]. In order to combine and synthesize two or more processes related to food supply networks, Yu and Nagurney contributed information on food products in supply chains [18]. The supply chain network optimal model for perishable goods has recently been the subject of numerous research articles from a system-optimization view. Wang and Li reduced food spoilage waste and maximize food retailer's profit through a pricing approach based on dynamically identified food shelf life [19]. Strengthening cold logistics infrastructure and adopting advanced decision-making tools can help optimize the supply chain and reduce

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food losses [20]. This study addresses the issue of quality loss in perishable product supply chain networks by taking into consideration the transportation time and rate of deterioration from the viewpoint of the user and contrasted it with fixed discount rates and dynamic pricing.

## 3. Objective of The Study

The objective is to incorporate stochastic demand forecasting and perishability constraints to balance supply and demand, optimize net profit, and compare fixed discount rate with dynamic pricing.

## 4. Methodology

### 4.1 Mathematical Modeling

To begin with consider a general network H = [G, L], where G denote node sets in the network and L denote directed link sets[21]. We build our supply chain model based on the framework[22]. The local collector and wholesaler formulations (Eq. 1–8) are taken from their model, with modifications later applied for Bangladeshi tomatoes.

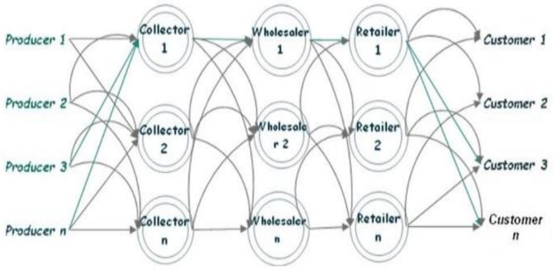


**Fig. 1** Supply chain network [22]

### 4.2 List of symbols

| Symbol | Denotation |
|---|---|
| s | Set of producers |
| l | Set of local collectors |
| i | Transportation way |
| j | Mode of transportation |
| $\gamma$(t) | Quality rate at time t |
| $\lambda$ | Rate of deterioration |
| $Q_s$ | Producer stock quantity(kg) |
| $P_s$ | Producer per unit selling price (BDT) |
| $Q_{sl}$ | Transferred quantity to local collector |
| $C_{sl}$ | Transportation cost per unit to local collector |
| $TC_{sl}$ | Producer-collector transaction cost |
| $P_l$ | Collector Unit Selling Price (BDT) |
| $Q_{ld}$ | Transferred quantity to wholesaler(kg) |
| $C_{ld}$ | Transportation cost per unit to wholesaler |
| $TC_{ld}$ | Local collector - wholesaler transaction cost |
| $P_d$ | Wholesaler Unit Selling Price (BDT) |
| $Q_{dr}$ | Transferred quantity to wholesaler(kg) |
| $C_{dr}$ | Transportation cost per unit to retailer |
| $TC_{dr}$ | Transaction cost b/n wholesaler &retailer |
| $P_r$ | Selling price per unit product at retailer |

### 4.3 Local Collector

Local collectors are individuals who buy perishable product directly from farmers in nearby village markets and then sell them to wholesalers. This relationship can be represented mathematically by the following equation

$$Q_l = \sum_{s=1}^{n} \sum_{i=1}^{j} Q_{sl} \tag{1}$$

The total transaction cost between a producer and a local collector includes both the transportation cost and the cost of discarding perishable products.

$$TC_{sl} = C_{sl}\left(Q_{sl}.\gamma(t)\right) \tag{2}$$

The total spoilage of products during transportation from producer to collector can be used to represent as a time-dependent function.

$$Q_{sl}^{s} = \left(1 - \gamma(t)\right) \tag{3}$$

The collector's profit is equal to the revenue from sales to wholesalers less the transaction and disposal expenses.

$$\text{Local Collector Profit} = \sum_{d}^{n} \sum_{i=1}^{j} \mathrm{P_l}.\gamma(t).\mathrm{Q_{ld}} - \sum_{s}^{n} \sum_{i=1}^{j} (\mathrm{TC_{sl}} + [\mathrm{Q_{sl}^{s}}.\mathrm{P_s}]) \tag{4}$$

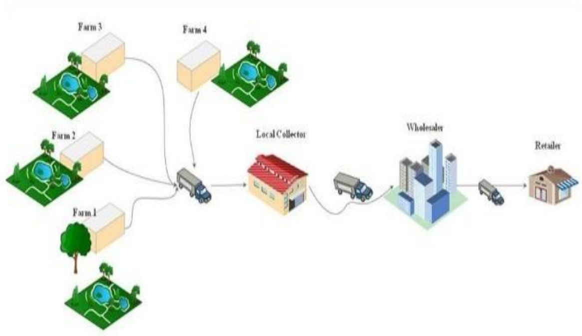

**Fig. 2** Tomato supply chain network [22]

### 4.4 Wholesaler

Local collectors sell their goods to wholesalers, and the amount that is transferred from collector $l$ to wholesaler $d$ establishes the overall amount of supply that can be distributed.

$$Q_d = \sum_{s=1}^{n} \sum_{i=1}^{j} Q_{ld} \tag{5}$$

The transaction cost includes transport and disposal of perishables.

$$TC_{ld} = C_{ld}\left(Q_{ld}.\gamma(t)\right) \tag{6}$$

The amount of product that spoils between the collector and wholesaler depends on time.

$$Q_{ld}^{s} = \left(1 - \gamma(t)\right).Q_d \quad (7)$$

Wholesaler profit equals sales revenue minus transaction and disposal costs.

$$\text{Wholesaler Profit} = \sum_{r}^{n}\sum_{i=1}^{j} P_d.\gamma(t).Q_{dr} - \sum_{s}^{n}\sum_{i=1}^{j}(TC_{ld} + [Q_{ld}^{s}.P_l]) \quad (8)$$

### 4.5 Retailer

Retailer demand depends on several factors that influence the demand rate of perishable products. These factors include market (a), price (p), and the quality rate at a given time (t).The model has adopted from literature[23]. The equation (9) provides the described demand.

$$D_1(t) = a - bp + d\gamma(t) + \varepsilon \quad 0 \le t \le t_0 \quad (9)$$

Here, b indicated price elasticity and d denotes product quality. ε denotes demand fluctuation and it is follow uniform distribution $\varepsilon \in U[-L, L]$. Based on quality loss, retailers provide a discount rate (θ), which results in the adjusted demand in (10).

$$D_2(t) = a - b\theta p + d\gamma(t) + f + \varepsilon \quad t_0 \le t \le T \quad (10)$$

### 4.6 Fixed Discount Rate and Retailer Profit

In this paper, a 50% discount rate is considered for analysis. Monte Carlo simulations were used to find the average daily profit for each scenario. This analysis considered factors like changing demand, perishability, spoilage, and transportation costs.

$$\text{Profit }(t) = P.\theta.D_2(t) - S * C_s - T_c * \left(S + D_2(t)\right) \quad (11)$$

here P = selling price per unit, θ = discount rate, S = unsold, $C_s$ = unsold cost per unit, $T_c$ = transportation cost per unit.

### 4.7 Dynamic Price Strategy and Retailer Profit

Unlike fixed discounts, many local sellers adjust prices dynamically based on freshness and demand conditions. This flexible pricing approach better reflects real market behavior, especially for highly perishable products, as it reduces waste and aligns prices with actual product quality and customer response. The model is adapted from [24]

$$P(t) = P_0.\left(\gamma(t)\right)^{\alpha} \quad (12)$$

In the dynamic pricing model, $P_0$ denotes the initial price and α controls the sensitivity of price to quality decay over time. Low values like α=0.5 cause prices to drop too quickly, reducing revenue, while higher values α=0.95 keep prices high but reduce revenue. Our analysis shows that α=0.8 provides the most balanced result the perishable product.

$$\text{Profit }(t) = P(t).D_2(t) - S * C_s - T_c * \left(S + D_2(t)\right) \quad (13)$$

### 4.8 Monte Carlo Simulation for Demand Uncertainty

Monte Carlo simulation is a computational technique that uses repeated random sampling to estimate the behavior of a system or process. In this paper, Monte Carlo simulation was used to reflect this uncertainty by randomly generating values for **ε** (the demand fluctuation term) over 1000 runs.

### 4.9 Numerical Example

The supply chain for perishable is examined in this research, as illustrated in figure 2. An exponential distribution is used to predict the quality rate of perishable. Quality rate has been adopted from literature[25] according to this formula.

$$\gamma(t) = q_0 e^{-\lambda t} \quad (14)$$

where λ and $q_0$ represents the rate of deterioration and initial quality, respectively.

**Table 1:** Different Parameters

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| a | 100 | d | 3 | θ | 0.5-0.6 | $P_l$ | 18 |
| b | 1.5 | $P_d$ | 25 | f | 3,7,10 | $P_r$ | 35 |
| $C_{ld}$ | 2 | $C_{dr}$ | 2 | ∈ | [-50,50] | Q | 100 |

**Table 2** Computational analysis at various λ values

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| λ | 0.05 | 0.07 | 0.09 | 0.11 | 0.13 | 0.17 | 0.2 |
| t | 0 | 3 | 6 | 10 | 15 | 18 | 20 |
| $\gamma(t)$ | 1 | 0.81 | 0.58 | 0.33 | 0.14 | 0.04 | 0.018 |

After testing various values, λ = 0.09 was selected because it best reflects tomato shelf-life under Bangladeshi post-harvest conditions. It captures the 4–5 days of freshness followed by gradual spoilage, avoiding unrealistic stability at lower values and premature decay at higher values. This choice ensures a realistic balance between freshness and spoilage, making the discount strategy and profit estimates more accurate.

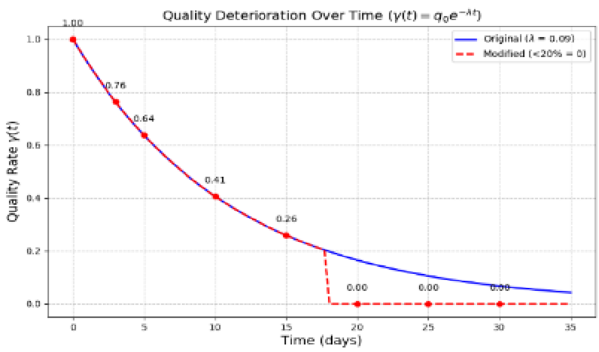


**Fig. 3** Quality rate at different time

When the quality rate γ(t) drops below 20%, the product is considered completely unsellable. For modeling purposes, values of γ(t)<0.2 are treated as zero to reflect total loss.

## 5. Result

This study explores how product quality, retailer pricing strategies, and time affect profit in a perishable supply chain. In this research paper, the retailer offers consumers a discount after 5 days. The results are based on simulations using both fixed discount rates and dynamic pricing models, combined with quality decay over time. As days pass, the quality of the product drops, and with it, demand and profit decrease. The findings clearly show that offering timely discounts and responding to quality levels can help reduce losses and improve decision-making. The following tables and graphs highlight how spoilage, and profit change across different stages of the supply chain.

**Table 3:** Computational study of quantity loss for multiple time points (t)

| Day | 0 | 3 | 6 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|
| $Q_{sl}^{s}$ | 0 | 24 | 42 | 60 | 76 | 100 |
| $Q_{ld}^{s}$ | 0 | 18 | 24 | 24 | 17 | 0 |
| $Q_r$ | 0 | 14 | 14 | 10 | 5 | 0 |

The values presented in this tables were generated using Equation (3) and Equation (7) from the model.

**Table 4:** Net profit computational result of the model

| Day | 0 | 3 | 6 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|
| Local | 1600 | 746 | 97 | -536 | -1066 | -1200 |
| Distributor | 2300 | 686 | -93 | -480 | -496 | 0 |
| Retailor | 3300 | 774 | -55 | -260 | -199 | 0 |
| Total profit | 7200 | 2206 | -51 | -1276 | -1761 | -1200 |

This table presents the profit results before applying the discount rate for each actor in the supply chain local collector, wholesaler, and retailer calculated using Equations (4) and (8), based on demand, pricing, and spoilage conditions at different time periods. The table shows negative profit, so the retailer offers discounts to generate profit.

**Table 5:** Retailer profit at 50% discount rate

| Day | Boost factor | Price | Avg. demand | profit |
|---|---|---|---|---|
| 6 | 3 | 17.5 | 78.32 | 628 |
| 7 | | | 78.57 | 639 |
| 8 | | | 77.72 | 598 |
| 9 | | | 78.46 | 634 |
| 10 | | | 77.72 | 603 |

Table 5 present retailer profit calculated using equation (13), where f=3 represents the demand boost factor to analyze how promotional impact affects profit under a dynamic pricing strategy. Monte Carlo simulation was used to generate average demand by running the model multiple times with random variations, making the results more realistic and robust.

The line graph 4 to show how retailer profit changes over time for 50% discount rates demand boost factors (f = 3, 7, 10). This results in higher profits, particularly when f=10, even in later days when product quality declines.

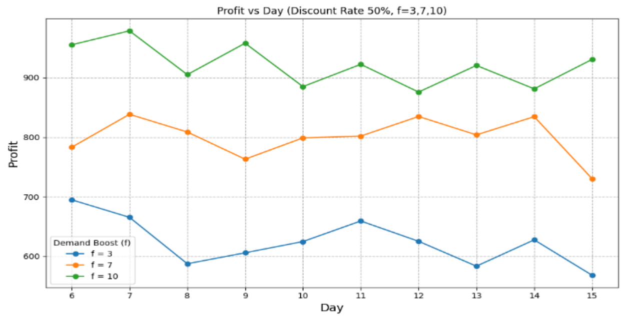


**Fig. 4** Effect of demand boost factor (f) on retailer profit at 50% discount Rate

**Table 6** Retailer profit at dynamic prices for demand boost factors f = 3

| Day | Boost factor | Price | Avg. demand | Profit |
|---|---|---|---|---|
| 6 | 3 | 22.72 | 71.62 | 718 |
| 7 | | 21.14 | 74.01 | 715 |
| 8 | | 19.67 | 74.84 | 643 |
| 9 | | 18.31 | 78.50 | 700 |
| 10 | | 17.04 | 78.26 | 589 |

Table 6, illustrate the evolution of retailer profit over time when dynamic pricing is applied in conjunction with varying levels of the demand boost factor (f). The underlying values were derived using Equation (12) for the demand function, equation (14) for dynamic pricing, and equation (15) for profit computation.


**Fig. 5** Retailer profit over time under dynamic pricing for demand boost factors f = 3, 7, and 10

The figure 5 graph show that under dynamic pricing, retailer profit declines over time as product quality decreases. However, higher demand boost factors (f = 7 and f = 10) help maintain stronger profits compared to lower values like f = 3. This suggests that customer engagement or promotion can offset the negative impact of spoilage.

### 5.1 Comparison of Dynamic Pricing and Fixed Discount Strategy (for f = 3)

To evaluate the financial advantage of dynamic pricing over fixed discounting, a relative improvement metric was calculated. For the demand boost factor f=3, the total retailer profit over Days 6 to 10 under dynamic pricing was 3365 BDT, compared to 3102 BDT under the fixed discount strategy.

Relative Improvement (%)

$$= \frac{\sum \text{Dynamic Profit} - \sum \text{Fixed Discount Profit}}{\sum \text{Fixed Discount Profit}} * 100$$

$$\text{Relative Imrovement (\%)} = \frac{3365 - 3102}{3102}$$

$$\text{Improvement} = 8.48\%$$

This means dynamic pricing earned approximately 8.48% more profit than fixed discounting for the same conditions. This 8.48% gain shows that dynamic pricing helps the retailer respond more effectively to changing product quality and customer demand.

## 6. Conclusion

This study focused on minimizing post-harvest losses in the tomato supply chain by modeling how quality, pricing, and customer demand interact over time. This study focused math and computer simulations to compare two pricing methods fixed discount and dynamic pricing. The results were pretty clear: dynamic pricing, particularly when combined with strategies to attract more buyers, helped sellers make more profit, even as the product got older. For instance, when demand was only slightly increased (like with f = 3), profits still went up by about 8.48% compared to the fixed discount method.

Future work can be done to enhance and expand this research in meaningful ways to incorporate delivery delays, storage practices, and cold-chain availability to better capture real-world conditions. These things really affect how fresh food stays. Also, this model isn't just for vegetables it could easily work for things like bananas, milk, or mangoes too. And to take it a step further, using tools like machine learning to better guess what people will buy, or pulling in live info from online shops, could really help. It'd just make the model smarter and more helpful for sellers who deal with this stuff every day.

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