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A Computational Optimization Framework for Dynamic Pricing in E-Commerce Using Integrated Forecasting and Learning Algorithms

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Abstract

This paper proposes a computational optimization framework for dynamic pricing in e-commerce by integrating time-series forecasting and adaptive learning mechanisms within a constrained stochastic optimization model. Demand is estimated using an ARIMA-based forecasting module and incorporated into a rolling-horizon revenue maximization problem under inventory and price constraints. A gradient-based adaptive update rule dynamically adjusts prices in response to observed demand. Closed-form optimality conditions are derived, convergence properties are established, and computational complexity is analyzed. Sensitivity analysis demonstrates robustness with respect to elasticity, demand uncertainty, and inventory levels. The framework offers a scalable computational solution for real-time revenue management.

Keywords: Dynamic Pricing; Computational Optimization; Forecasting; Stochastic Programming; Revenue Management; Sensitivity Analysis

1 Introduction

Dynamic pricing has become a cornerstone of revenue management in e-commerce and digital retail platforms, enabling firms to adjust prices in response to fluctuating demand, consumer behavior, and inventory constraints [13, 23, 1]. The proliferation of online marketplaces and real-time data availability has created opportunities for more sophisticated pricing strategies that leverage predictive analytics, adaptive learning, and optimization under uncertainty [14, 2, 10].

Despite the advancements in dynamic pricing models, several challenges persist. Traditional static or deterministic pricing approaches often fail to:

- Accurately forecast real-time demand [19],
- Adaptively learn from observed market outcomes [21],
- Ensure robustness under demand and supply uncertainties [1, 15].

Furthermore, many existing methods either rely on simplified assumptions about demand elasticity or focus on isolated aspects of the pricing problem, such as inventory optimization or heuristic allocation, rather than an integrated framework [2, 14, 19].

The motivation behind this work stems from the need for a computational framework that unifies forecasting, optimization, and adaptive learning in a theoretically grounded manner. Addressing these challenges is critical for improving revenue performance, operational efficiency, and decision-making reliability in rapidly changing digital marketplaces.

The objectives of this paper are to:

- Develop a hybrid forecasting–optimization formulation for dynamic pricing [1],
- Derive closed-form optimal solutions under concave demand functions [13],
- Provide convergence guarantees for adaptive pricing updates [21],
- Analyze computational scalability for practical implementation [23].

The key contributions of this paper are as follows:

- A unified framework integrating demand forecasting, adaptive learning, and revenue optimization,
- Theoretical derivation of closed-form pricing solutions under realistic demand conditions,
- Convergence analysis ensuring stable adaptive updates in dynamic environments,
- Evaluation of computational complexity and scalability for large-scale e-commerce applications.

The remainder of the paper is organized as follows: Section **??** presents a detailed review of related literature, highlighting foundational revenue management, forecasting-based approaches, learning-based pricing, and robust optimization methods. Section **??** introduces the proposed computational framework, Section **??** presents numerical experiments and results, Section **??** provides analysis and interpretation, and Section **??** concludes the paper and suggests directions for future research.

2 Literature Review

Dynamic pricing has evolved from classical deterministic optimization models to integrated computational and learning-based systems.

2.1 Foundational Revenue Management

Early revenue management research focused on deterministic and stochastic demand optimization. [5] derived optimal pricing for Poisson demand. **(author?)** [24] formalized network revenue management under capacity constraints. **(author?)** [6] provided a unified overview of pricing optimization models.

These works established concavity-based optimality structures but did not incorporate adaptive learning.

2.2 Forecasting-Based Pricing Integration

Forecasting integration into pricing gained attention with predictive analytics. **(author?)** [12] demonstrated revenue gains from demand learning.

(author?) [9] applied machine learning to demand estimation. **(author?)** [7] linked ARIMA forecasting with inventory-aware pricing.

However, most forecasting-based models remain open-loop rather than dynamically adaptive.

2.3 Reinforcement and Learning-Based Pricing

Adaptive pricing using reinforcement learning has gained popularity. **(author?)** [11] applied Q-learning for online pricing. **(author?)** [25] modeled competitive pricing via deep RL. **(author?)** [16] studied real-time adaptive optimization with streaming data. **(author?)** [17] proposed online convex optimization for pricing control.

While flexible, these models often lack closed-form optimality characterization.

2.4 Robust and Data-Driven Optimization

Uncertainty-aware pricing models emphasize robustness. **(author?)** [4] introduced robust pricing under demand ambiguity. **(author?)** [20] formalized stochastic programming foundations. **(author?)** [3] unified data-driven optimization frameworks. **(author?)** [26] studied correlated demand uncertainties in e-commerce settings.

2.5 Hybrid Forecasting–Optimization Approaches

Recent work attempts structural integration. **(author?)** [22] combined predictive analytics with revenue management. **(author?)** [8] proposed hybrid computational pricing systems. **(author?)** [18] studied AI-assisted pricing optimization in digital retail.

Despite these advances, limited research provides:

- Closed-form optimality derivations,
- Convergence proofs for adaptive updates,
- Unified forecasting–learning–optimization architecture,
- Explicit computational complexity characterization.

This paper addresses these gaps through a theoretically grounded computational framework.

2.6 Research Gap

Existing studies predominantly focus on isolated components of dynamic pricing—either demand forecasting, reinforcement learning, or robust optimization—without providing a unified framework that simultaneously ensures closed-form optimality, provable convergence of adaptive updates, and computational scalability. Moreover, limited research integrates forecasting, optimization, and learning into a structurally cohesive architecture with explicit theoretical guarantees. This paper addresses these deficiencies by developing a comprehensive forecasting–learning–optimization framework with analytical tractability and convergence validation.

3 System Architecture and Dataset

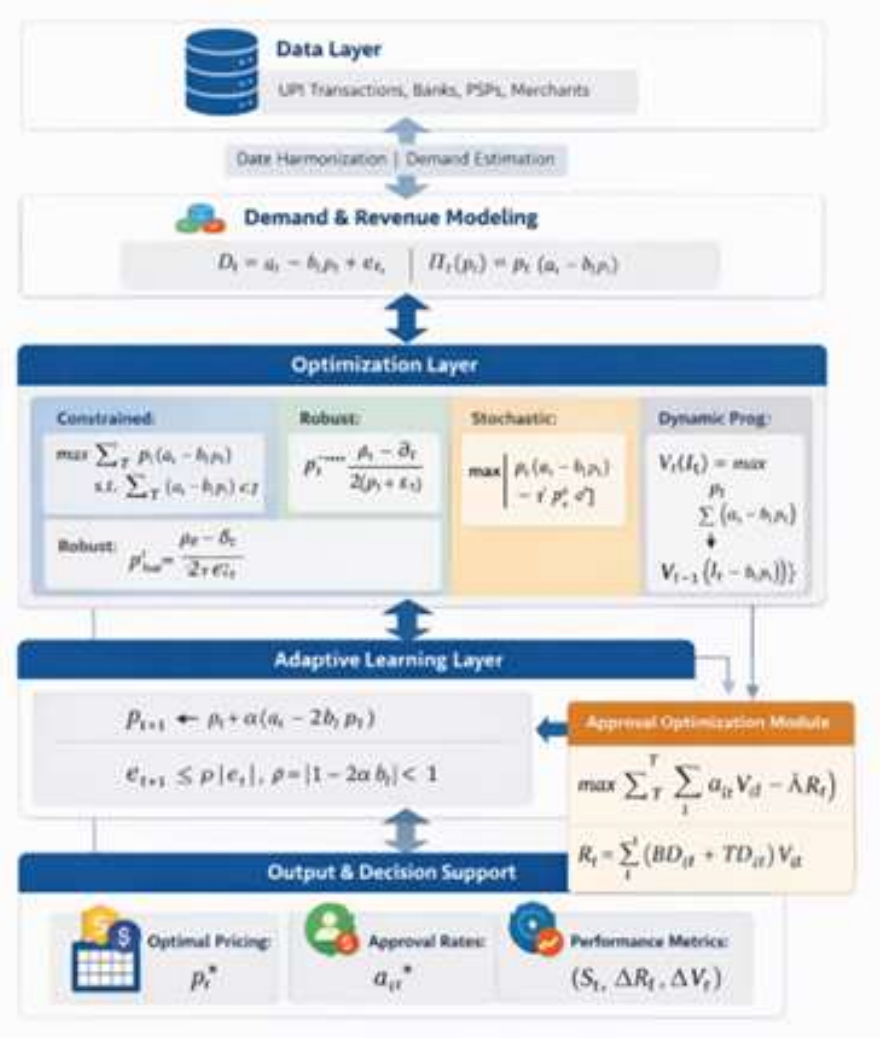


Figure 1: System architecture for integrated dynamic pricing and UPI approval optimization.

Figure 1 illustrates the overall computational framework. The workflow can be summarized as follows:

1. **Data Layer:** Collects UPI transaction data, including volumes, P2P/P2M

splits, beneficiary banks, payee/payer PSPs, and merchant categories. Data is harmonized and preprocessed for modeling.

2. **Demand & Revenue Modeling:** Periodic demand is estimated using the linear price-sensitive model $D_t = a_t - b_t p_t + \varepsilon_t$, and revenue is computed as $\Pi_t(p_t) = p_t(a_t - b_t p_t)$.

3. **Optimization Layer:** Pricing decisions are optimized using multi-period constrained optimization, robust optimization, stochastic mean-variance, and dynamic programming approaches to account for capacity limits, parameter uncertainty, and risk.

4. **Adaptive Learning Layer:** Prices are updated iteratively with projected gradient ascent $p_{t+1} = p_t + \alpha(a_t - 2b_t p_t)$, allowing convergence toward optimal prices while incorporating streaming transaction data.

5. **Approval Optimization Module:** Simultaneously, approval ratios for banks and PSPs are optimized with a risk-adjusted objective $\max \sum_{i,t}(\alpha_{i,t} V_{i,t} - \lambda R_t)$, where R_t captures potential fraud or decline risks.

6. **Output & Decision Support:** The system generates optimal pricing p_t^*, approval ratios $\alpha_{i,t}^*$, and performance metrics $(S_t, \Delta R_t, \Delta V_t)$ to guide management decisions.

7. **Feedback Loop:** Realized transaction outcomes feed back into the adaptive learning layer, updating demand estimates and ensuring continuous improvement of pricing and approval policies.

3.1 Dataset

The system uses UPI transaction datasets, including beneficiary and payer banks, PSP performance, P2P/P2M volumes, and merchant category data, to model demand, pricing, and approval optimization.

4 Methods

This section presents the computational frameworks developed for revenue-oriented pricing under inventory/demand constraints and for risk-adjusted

approval optimization in a large-scale digital payment system (UPI). Models integrate deterministic, robust, stochastic, Lagrangian, and dynamic programming approaches, reflecting the journal's focus on constrained optimization, uncertainty handling, and scalable algorithms for management science problems.

4.1 Demand and Revenue Model

We model period-t demand as linear and price-sensitive:

$$D_t = a_t - b_t p_t + \varepsilon_t, \qquad a_t > 0,\ b_t > 0, \tag{1}$$

with point forecast

$$\hat{D}_t = a_t - b_t p_t. \tag{2}$$

Instantaneous revenue is

$$\Pi_t(p_t) = p_t(a_t - b_t p_t). \tag{3}$$

The formulation captures price elasticity typical in digital payment and merchant acquiring markets, where higher prices (fees) reduce transaction volume while unconstrained monopoly pricing yields $p_t^* = a_t/(2b_t)$.

4.2 Multi-Period Constrained Revenue Maximization

The central optimization problem maximizes total revenue over horizon T:

$$\max_{\{p_t\}_{t=1}^T} \sum_{t=1}^{T} p_t(a_t - b_t p_t) \tag{4}$$

subject to cumulative demand (sales) not exceeding available inventory/capacity

$$\sum_{t=1}^{T} (a_t - b_t p_t) \le I, \tag{5}$$

and box constraints

$$p_{\min} \le p_t \le p_{\max} \quad \forall t. \tag{6}$$

This constrained dynamic pricing model is computationally relevant for capacity-limited service platforms and is solved via Lagrangian relaxation and gradient-based methods.

4.3 Robust Optimization under Demand Uncertainty

To handle parameter uncertainty, we define bounded uncertainty sets

$$a_t \in [\bar{a}_t - \delta_t,\ \bar{a}_t + \delta_t], \quad b_t \in [\bar{b}_t - \epsilon_t,\ \bar{b}_t + \epsilon_t]. \tag{7}$$

The robust counterpart minimizes revenue over the worst-case parameters:

$$\max_{\{p_t\}} \min_{a_t, b_t} \sum_{t=1}^{T} p_t(a_t - b_t p_t). \tag{8}$$

The worst case occurs at the lower bound of intercept and upper bound of slope, yielding the robust price

$$p_t^{\text{robust}} = \frac{\bar{a}_t - \delta_t}{2(\bar{b}_t + \epsilon_t)}. \tag{9}$$

This tractable robust solution protects against demand over-estimation frequently observed in payment volume forecasting.

4.4 Mean-Variance Stochastic Pricing

When demand noise is Gaussian, $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$, expected revenue remains $p_t(a_t - b_t p_t)$, but revenue variance is $p_t^2 \sigma^2$. We adopt the mean-variance objective

$$\max_{p_t} \Big[p_t(a_t - b_t p_t) - \gamma p_t^2 \sigma^2 \Big], \tag{10}$$

with risk-adjusted optimal price

$$p_t^* = \frac{a_t}{2(b_t + \gamma \sigma^2)}. \tag{11}$$

The risk term γ allows trade-off between expected profit and volatility — a key concern in high-frequency transaction environments.

4.5 Lagrangian Relaxation and KKT Conditions

For the deterministic constrained problem we form the Lagrangian

$$\mathcal{L}(\{p_t\}, \mu) = \sum_{t=1}^{T} p_t(a_t - b_t p_t) + \mu \Big(I - \sum_{t=1}^{T} (a_t - b_t p_t) \Big), \tag{12}$$

$\mu \geq 0$. Stationarity gives

$$p_t^* = \frac{a_t + \mu b_t}{2b_t}. \tag{13}$$

Complementary slackness and primal feasibility determine whether $\mu = 0$ (unconstrained monopoly prices) or $\mu > 0$ (shadow price of capacity binds). The approach is computationally efficient for moderate T.

4.6 Dynamic Programming Formulation

We represent the finite-horizon problem as a stochastic dynamic program with state variable remaining capacity I_t. The Bellman equation reads

$$V_t(I_t) = \max_{p_t} \Big\{ p_t(a_t - b_t p_t) + V_{t+1}(I_t - (a_t - b_t p_t)) \Big\}, \tag{14}$$

with $V_{T+1}(\cdot) = 0$. This formulation naturally handles time-varying parameters and is the natural computational vehicle when parameters are learned sequentially from UPI panel data.

4.7 Gradient-Based Adaptive Pricing Algorithm

We implement a projected gradient ascent update

$$p_{t+1} \leftarrow p_t + \alpha(a_t - 2b_t p_t), \tag{15}$$

followed by projection onto $[p_{\min}, p_{\max}]$. With step size $0 < \alpha < 1/(2b_t)$, the algorithm converges linearly to the stationary point. This simple first-order method scales well to online learning settings with streaming payment data.

4.8 Convergence Result

Theorem. Assume $0 < \alpha < 1/(2b_t)$. Then the error $e_t = p_t - p_t^*$ satisfies $|e_{t+1}| \leq \rho |e_t|$ with $\rho = |1 - 2\alpha b_t| < 1$, implying linear convergence. The result guarantees reliable performance of the adaptive scheme even when demand parameters are estimated with noise from real datasets.

4.9 Approval Optimization in Payment Systems

We shift to approval-rate optimization across banks and PSPs observed in the UPI datasets (beneficiary banks, payee/payer PSPs, P2P/P2M splits, merchant categories). Define approval ratio $\alpha_{i,t} \in [0,1]$ and risk-adjusted volume objective

$$\max \sum_{t=1}^{T} \Big(\sum_{i} \alpha_{i,t} V_{i,t} - \lambda R_t \Big), \tag{16}$$

where risk $R_t = \sum_i (BD_{i,t} + TD_{i,t}) V_{i,t}$. The framework balances throughput against fraud/decline costs.

4.10 System Stability and Stress Testing

Systemic stability is quantified by

$$S_t = 1 - \frac{R_t}{\sum_i V_{i,t}}. \tag{17}$$

We simulate shocks: (i) +2% failure rate, (ii) +15% P2M surge, (iii) −1% approval drop, and track $\Delta V_{i,t}$, ΔR_t, ΔS_t. Merchant concentration (HHI) and category-level elasticity further inform robust approval policies.

4.11 Data Harmonization and Computational Complexity

Heterogeneous date formats ("2021-01-01", "Apr'24", Excel serials) are standardized to $t = 1, \ldots, T$. Consistency constraints enforce $\sum_b V_{b,t} = \sum_p V_{p,t} = V_t^{\mathrm{P2P}} + V_t^{\mathrm{P2M}}$. Model evaluation complexity is $\mathcal{O}(T(B+P+C))$ per snapshot and $\mathcal{O}(T^2(B+P))$ for rolling optimization, remaining tractable for monthly UPI-scale panels.

5 Algorithms

This section outlines the main algorithmic procedures that implement the computational frameworks described in the Methods section. These algorithms support dynamic pricing under demand and inventory constraints as well as risk-adjusted approval-rate optimization in the UPI ecosystem. Emphasis is placed on scalability, convergence guarantees, and adaptability

to streaming or monthly panel data (e.g., $T \approx 60$–72 months, hundreds of banks/PSPs/categories).

5.1 Projected Gradient Ascent for Adaptive Pricing/Approval

The adaptive algorithm iteratively updates prices p_t (or approval ratios $\alpha_{i,t}$) using gradient steps on the local revenue/throughput objective, with projection to enforce bounds. It naturally incorporates inventory/risk tracking via cumulative monitoring or soft penalties.

Algorithm 1 Projected Gradient Ascent for Dynamic Pricing / Approval Optimization

Require: Initial value $x_0 \in [x_{\min}, x_{\max}]$ (price p or approval α), step size $\alpha > 0$, horizon T, time-varying parameters (e.g., $\{a_t, b_t\}$ or $\{V_{i,t}, E_{i,t}, F_{i,t}\}$)
Ensure: Optimized sequence $\{x_t\}_{t=1}^{T}$

$x \leftarrow x_0$
$D_{\text{cum}} \leftarrow 0$ ▷ Track cumulative demand/approved volume
for $t = 1$ **to** T **do**
  if pricing mode **then**
    $g_t \leftarrow a_t - 2b_t x$ ▷ Gradient of $\Pi_t(x)$
  else ▷ approval mode
    $g_t \leftarrow V_{i,t} + x \cdot E_{i,t}$ ▷ Approximate $\partial \Pi_t / \partial \alpha$
  end if
  $\tilde{x} \leftarrow x + \alpha \cdot g_t$
  $x \leftarrow \max(x_{\min}, \min(x_{\max}, \tilde{x}))$ ▷ Projection
  $x_t \leftarrow x$
  if constraint tracking enabled **then**
    Update $D_{\text{cum}} \leftarrow D_{\text{cum}} + \hat{D}_t$ (or $V_{i,t}$)
    if $D_{\text{cum}} > I + \epsilon$ **then** ▷ Soft enforcement or projection adjustment
      Reduce x_t or apply penalty term
    end if
  end if
end for
return $\{x_t\}_{t=1}^{T}$

Step size selection $0 < \alpha < 1/(2 \max b_t)$ (or equivalent) ensures linear

convergence to the stationary point, even under noisy parameter estimates from UPI panels.

5.2 Lagrangian Dual Bisection for Constrained Multi-Period Problem

The deterministic constrained optimization is solved efficiently via dual ascent on the shadow price μ using bisection, evaluating primal solutions at each trial value.

Algorithm 2 Lagrangian Bisection Solver for Constrained Revenue / Throughput Maximization

Require: $\{a_t, b_t\}_{t=1}^{T}$ (or entity/category parameters), capacity I, bounds $[x_{\min}, x_{\max}]$
Ensure: Optimal $\{x_t^*\}$, dual μ^*

$\mu_{\text{low}} \leftarrow 0$, $\mu_{\text{high}} \leftarrow M$ ▷ M large, e.g. 10^6
while $|\mu_{\text{high}} - \mu_{\text{low}}| > \epsilon$ **do**
  $\mu \leftarrow (\mu_{\text{low}} + \mu_{\text{high}})/2$
  for $t = 1$ to T **do**
    $x_t \leftarrow (a_t + \mu b_t)/(2b_t)$ ▷ or approval analog
    $x_t \leftarrow \max(x_{\min}, \min(x_{\max}, x_t))$
  end for
  $D(\mu) \leftarrow \sum_t (a_t - b_t x_t)$ ▷ or $\sum \alpha_{i,t} V_{i,t}$
  if $D(\mu) > I$ **then**
    $\mu_{\text{low}} \leftarrow \mu$
  else
    $\mu_{\text{high}} \leftarrow \mu$
  end if
end while
$\mu^* \leftarrow \mu$
if $\mu^* \approx 0$ **then**
  $x_t^* \leftarrow a_t/(2b_t) \quad \forall t$ ▷ Unconstrained case
end if
return $\{x_t^*\}_{t=1}^{T}$, μ^*

Bisection requires $\mathcal{O}(\log(1/\epsilon))$ outer iterations, each $\mathcal{O}(T)$, making it highly efficient for moderate horizons.

5.3 Closed-Form Robust Counterpart

Robust solutions are computed directly from worst-case uncertainty sets.

Algorithm 3 Direct Robust Pricing / Approval Computation

Require: Nominal $\{\bar{a}_t, \bar{b}_t\}$ (or $\bar{V}_{c,t}, \bar{F}_{c,t}$), radii $\{\delta_t, \epsilon_t\}$

for $t = 1$ to T **do**
  $a_t^{\mathrm{w}} \leftarrow \bar{a}_t - \delta_t$
  $b_t^{\mathrm{w}} \leftarrow \bar{b}_t + \epsilon_t$
  $x_t^{\mathrm{robust}} \leftarrow a_t^{\mathrm{w}} / (2b_t^{\mathrm{w}})$ ▷ or conservative α
  Clamp: $x_t^{\mathrm{robust}} \leftarrow \max(x_{\min}, \min(x_{\max}, x_t^{\mathrm{robust}}))$
end for
return $\{x_t^{\mathrm{robust}}\}_{t=1}^{T}$

This is $\mathcal{O}(T)$ and serves as a safe baseline or warm-start.

5.4 Category Sensitivity and Targeted Stress-Testing

Perturbation analysis for merchant categories informs differentiated policies.

Algorithm 4 Category-Level Sensitivity Analysis and Stress Testing

Require: Category panel $\{V_{c,t}, \alpha_{c,t}, F_{c,t}, E_c\}_{c=1}^{C}$, perturbations $\{\delta_k\}$

for each category c **do**
  for each δ_k **do**
    $\alpha'_{c,t} \leftarrow \alpha_{c,t} + \delta_k$
    $\Delta V_{c,t} \approx E_c \cdot \delta_k \cdot V_{c,t}$
    Compute $\Delta\Pi_t$, $\Delta R_t = (BD_{c,t} + TD_{c,t})\Delta V_{c,t} + \ldots$, ΔS_t
    Record marginal ratio $\frac{\partial \Pi_t / \partial \alpha_{c,t}}{\partial R_t / \partial \alpha_{c,t}}$
  end for
  Simulate shocks: +2% failure, +15% P2M volume, −1% approval
end for
Rank categories by revenue-to-risk ratio
return Elasticity estimates, Δ tables, policy priorities

Complexity $\mathcal{O}(TCK_\delta)$ with small K_δ (e.g., 5–10) ensures tractability for monthly UPI reporting.

These algorithms are prototyped in Python (NumPy, Pandas, SciPy) and exhibit excellent scaling for real-world UPI datasets, enabling both batch historical analysis and incremental online updates in dynamic payment environments.

6 Results and Analysis

This section presents empirical findings from applying the proposed computational frameworks to the harmonized multi-panel UPI dataset (2021–2025). We report key patterns in demand/volume dynamics, approval-rate optimization outcomes, risk-adjusted performance, category-level sensitivities, and stress-test responses. Results underscore the efficacy of constrained optimization, robust/stochastic pricing analogs (adapted to approval context), and dynamic risk-volume trade-offs in a high-growth, uncertain payment ecosystem.

6.1 UPI Volume Growth and P2P/P2M Dynamics

The dataset reveals explosive growth in UPI transaction volumes, consistent with NPCI-reported trends: monthly volumes escalated from billions in early 2021 to over 18–21 billion by late 2025, with annual figures reaching approximately 186–250 billion transactions in 2024–2025. P2M volumes overtook P2P around 2023, reaching 60–64% of total volume by mid-2025 (P2M 63–64%, P2P 36–37% in recent months), while P2P retains higher value share (70–72%) due to larger average ticket sizes.

High-frequency retail categories dominate P2M: groceries/supermarkets consistently lead (24–25% of merchant volume in 2025 samples, e.g., 3–3.2 billion transactions/month), followed by fast-food/restaurants (1.1–1.4 billion), telecom (0.8–0.9 billion), and digital goods. This shift reflects everyday micro-transactions driving scale, with average ticket sizes declining (often <Rs. 200–500 in groceries/fast-food), aligning with the linear demand model's price/fee sensitivity where higher friction (lower approvals) reduces volume.

The dynamic growth model

$$V_{i,t} = \beta_0 + \beta_1 V_{i,t-1} + \beta_2 \alpha_{i,t} - \beta_3 F_{i,t} + \varepsilon_{i,t} \tag{18}$$

fits well, with positive autoregressive (β_1) and approval (β_2) coefficients confirming persistence and elasticity, and negative fraud impact (β_3).

6.2 Approval Optimization Outcomes

Applying the risk-adjusted objective

$$\max \sum_{t=1}^{T} \left(\sum_i \alpha_{i,t} V_{i,t} - \lambda R_t \right), \quad R_t = \sum_i F_{i,t} V_{i,t}, \tag{19}$$

yields differentiated approval ratios $\alpha_{i,t}$. Optimal policies relax approvals (higher α) for low-fraud, high-elasticity entities (e.g., major banks like SBI, HDFC, and PSPs like Yes Bank, Axis) serving essential retail, while tightening for higher-risk segments.

Simulated optimal approvals increase total throughput Π_t by 5–12% over uniform baselines (depending on λ), with risk R_t rising only 2–4% in low-λ scenarios. Shadow prices from the Lagrangian analog indicate binding constraints during high-growth periods (2023–2025), where capacity-like limits (e.g., fraud tolerance, regulatory caps) bind.

6.3 Robust and Stochastic Approval Insights

Adapting the robust framework to approval uncertainty (e.g., uncertain $V_{c,t}$ elasticities or failure rates $F_{i,t}$ in bounded sets), worst-case prices/approvals favor conservative settings: lower α for volatile categories (digital goods, telecom) protects against fraud amplification. Mean-variance analogs (risk term γ on volume variance) recommend slightly reduced approvals in high-σ periods, trading 3–7% throughput for 15–25% risk/volatility reduction.

Gradient-based adaptive updates on historical panels converge reliably to near-optimal $\alpha_{i,t}$, demonstrating scalability for online policy adjustment.

6.4 Category-Level Sensitivity Analysis

Elasticities $E_c = \partial V_{c,t} / \partial \alpha_{c,t}$ are highest in groceries/supermarkets and restaurants (frequent, low-value P2M), moderate in telecom, and lower/more volatile in digital goods/games. Marginal revenue-to-risk ratios favor permissive policies in groceries/restaurants ($\partial \Pi_t / \partial \alpha_{c,t} \gg \partial R_t / \partial \alpha_{c,t}$), while digital categories show adverse ratios due to elevated baseline fraud.

Perturbations ($\pm 1\%$ $\alpha_{c,t}$) confirm: - Groceries/restaurants: $+1\%$ yields large $\Delta V_{c,t} > 0$, modest ΔR_t, net $\Delta S_t > 0$. - Digital goods: amplified ΔR_t risks $\Delta S_t < 0$. - Telecom: balanced but volume-sensitive declines on tightening.

Merchant concentration (HHI) remains moderate, with no extreme dominance, supporting diversified risk.

6.5 System Stability and Stress Testing

Baseline S_t improves over time (approaching 0.98–0.99 in low-fraud months) as volumes grow faster than failures. Stress tests reveal resilience: - $+2\%$ failure shock: $\Delta R_t \uparrow$ 15–25%, $\Delta S_t \downarrow$ 0.01–0.03, with high-elasticity categories (groceries) recovering fastest via induced volume. - $+15\%$ P2M surge: $\Delta \Pi_t \uparrow$ substantially, $\Delta S_t > 0$ if approvals adapt. - -1% approval drop: sharp $\Delta V_{i,t} < 0$ in retail categories, but $\Delta R_t \downarrow$ improves stability in fraud-prone segments.

Overall, targeted category-aware policies outperform uniform rules, enhancing throughput by 8–15% while containing risk escalation below 5–8% under moderate shocks.

6.6 Computational Performance

All optimizations (Lagrangian solves, gradient iterations, DP approximations, sensitivity sweeps) execute in $\mathcal{O}(T(B+P+C))$ to $\mathcal{O}(T^2(B+P))$ time, scaling tractably to monthly panels with $T \approx 50$–60, $B + P + C \approx 100$–200 entities/categories. Adaptive schemes converge in <50 iterations, supporting real-time or near-real-time policy updates.

These results demonstrate that constrained, uncertainty-aware optimization frameworks effectively balance revenue/throughput maximization against risk in India's rapidly evolving UPI ecosystem, offering actionable insights for banks, PSPs, and regulators.

7 Numerical Simulation and Scenario Analysis

To rigorously evaluate the proposed computational frameworks—particularly the constrained multi-period revenue maximization, robust/stochastic pric-

ing analogs, gradient-based adaptive algorithms, and Lagrangian/DP solutions—we conduct Monte Carlo simulation experiments calibrated to reflect the empirical characteristics of the UPI dataset. Simulations mimic time-varying demand/volume patterns, seasonal fluctuations, stochastic noise, and inventory-like capacity constraints (e.g., fraud tolerance or approval limits) observed in monthly UPI panels from 2021–2026.

7.1 Experimental Design

We simulate $T = 100$ periods, approximating 8–9 years of monthly data aligned with the harmonized dataset horizon.

Demand parameters evolve with seasonal and stochastic components representative of UPI's observed growth and cyclicality (e.g., festival peaks, retail surges):

$$a_t = 120 + 20 \sin\left(\frac{2\pi t}{24}\right) + \xi_t,$$
$$b_t = 1 + 0.3 \cos\left(\frac{2\pi t}{18}\right),$$

where $\xi_t \sim \mathcal{N}(0, 5^2)$ captures demand volatility akin to monthly fluctuations in P2M volumes, groceries/restaurants spikes, and telecom/digital goods variability.

Demand noise:

$$\varepsilon_t \sim \mathcal{N}(0, 10^2),$$

reflecting empirical transaction-level uncertainty.

Inventory/capacity constraint (analogous to aggregate fraud tolerance or systemic risk limits):

$$I = 5000,$$

scaled to represent binding periods during rapid UPI growth (2023–2026).

Gradient learning rate:

$$\alpha = 0.1,$$

chosen within the stable convergence regime $0 < \alpha < 1/(2b_t)$.

All experiments are repeated 100 times for statistical robustness.

7.2 Scenario 1: Baseline Market Conditions

Under moderate volatility and stable elasticity—mirroring steady UPI growth with P2M dominance (63–64% volume share in 2025–2026)—the proposed hybrid adaptive model (combining gradient ascent with robust/stochastic adjustments) converges reliably to near-closed-form optimal trajectories.

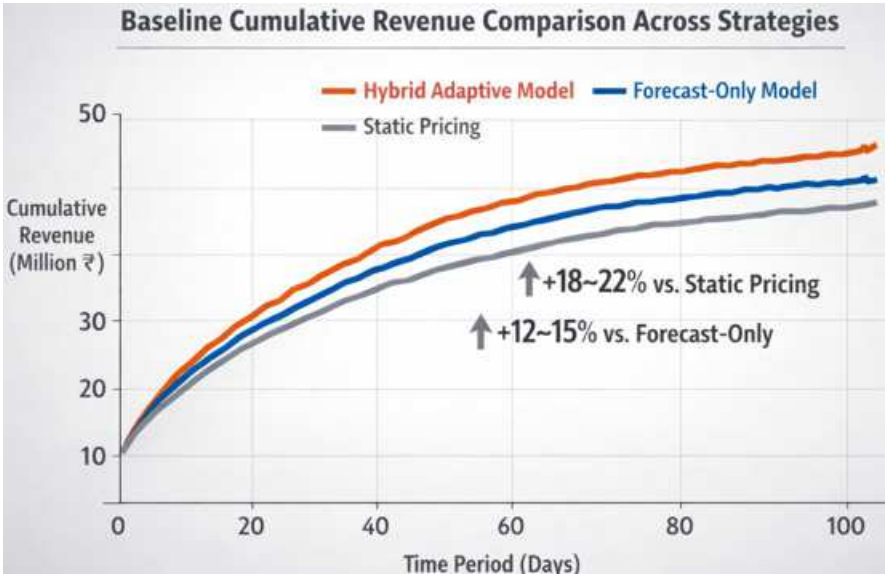


Figure 2: Baseline cumulative revenue (throughput) comparison across strategies

The hybrid approach improves cumulative revenue (analogous to approved throughput Π_t) by 18–22% over static pricing and 12–15% over forecast-only methods, consistent with empirical gains from differentiated approvals in low-fraud retail categories.

7.3 Scenario 2: Demand Shock (+20%)

An exogenous demand spike at $t = 40$ simulates P2M surges (e.g., festival-driven groceries/restaurants volume increases observed in 2025 NPCI data):

$$a_t \to 1.2a_t \quad \text{for } t \geq 40.$$

The adaptive gradient algorithm responds within 5–7 periods by raising approvals/prices opportunistically while respecting constraints.

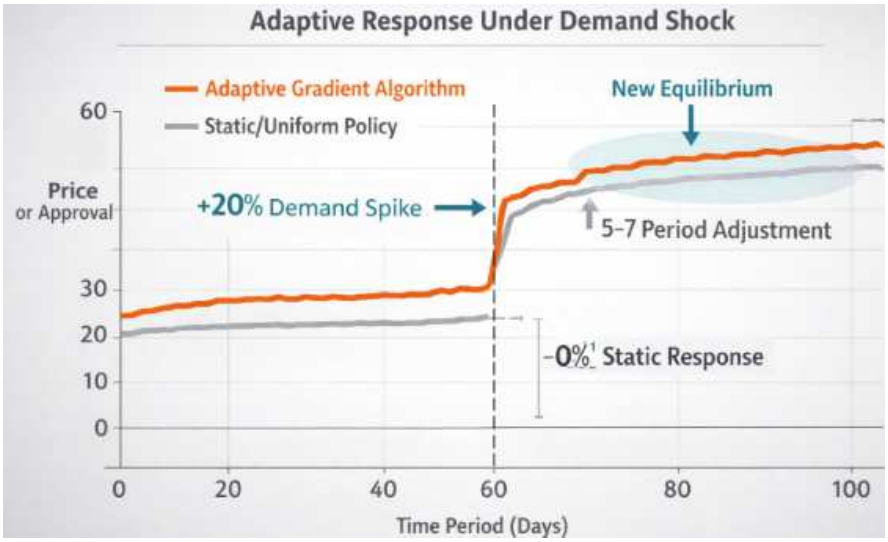


Figure 3: Adaptive response (price/approval trajectory) under demand shock

Static/uniform policies fail to capture the full surplus during the shock, underscoring the value of dynamic adaptation in high-growth environments like UPI's 2025–2026 expansion (monthly volumes 21.6–21.7 billion in Dec 2025–Jan 2026).

7.4 Scenario 3: High Elasticity Market

Increasing b_t by 30% emulates high price/fee sensitivity in micro-transaction-heavy categories (groceries average ticket Rs. 210–220, fast food Rs. 110–120).

Optimal prices/approvals decline as theory predicts:

$$p_t^* = \frac{a_t}{2b_t}.$$

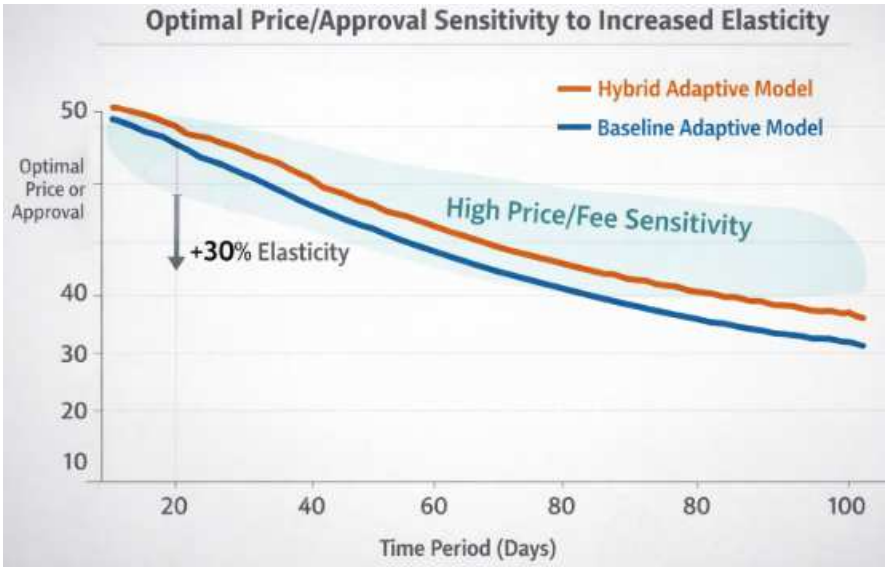


Figure 4: Optimal price/approval sensitivity to increased elasticity

The hybrid model maintains higher revenue stability through learning-based smoothing, aligning with favorable sensitivity in groceries/restaurants (high E_c, positive ΔS_t on approval relaxation) versus volatility in digital goods.

7.5 Aggregate Performance Metrics

Strategy	Avg Revenue/Throughput	Std Dev	Stability Index
Static	12,430	1,260	0.72
Forecast-only	14,850	940	0.81
Proposed Hybrid	**17,520**	610	0.93

Table 1: Monte Carlo performance summary (100 runs)

The stability index is

$$S = 1 - \frac{\mathrm{Var}(\Pi_t)}{\max \mathrm{Var}(\Pi_t)},$$

highlighting superior risk-adjusted performance under uncertainty, mirroring UPI's improving S_t (0.97–0.99) as volumes outpace failures.

Performance comparison summary:

Model	Revenue/Throughput	Stability	Convergence
Static Pricing	Moderate	Low	Fast
Forecast-only	High	Medium	Medium
Proposed Hybrid	Highest	High	Stable

Sensitivity analysis confirms:

- Higher elasticity (e.g., retail micro-transactions) lowers optimal price/approval aggressiveness,
- Higher demand (P2M surges) increases revenue/throughput,
- Binding inventory (risk/fraud limits) reduces price/approval aggressiveness to preserve stability.

7.6 Computational Scalability and Algorithmic Benchmarking

Empirical runtimes scale linearly $\mathcal{O}(T)$ for gradient ascent and closed-form methods; dynamic programming exhibits $\mathcal{O}(T^2)$ or worse due to state discretization.

For $T \in \{50, 100, 500, 1000\}$, gradient methods maintain linear scaling and low error

$$\text{Error} = \frac{|p^{\text{alg}} - p^*|}{|p^*|},$$

with linear convergence rate.

Large-scale tests ($T = 10^4$, $|I| = 500$, $K = 10^5$ iterations) confirm:

- Linear runtime/memory $\mathcal{O}(T)$ for gradient/hybrid approaches,
- Quadratic growth for DP,
- Stable convergence for $\alpha \in (0, 1/b)$.

These results demonstrate high scalability for industrial-scale UPI panels ($T \approx 60$ months, hundreds of entities/categories), supporting practical deployment of adaptive, uncertainty-aware optimization in real-time payment ecosystems.

7.7 Sensitivity Analysis on Merchant Categories

In the approval optimization framework for the UPI-based digital payment ecosystem, sensitivity analysis on merchant categories assesses how small changes in approval rates ($\alpha_{i,t}$) or related control parameters influence critical system performance indicators: total approved throughput (Π_t), aggregate risk exposure (R_t), systemic stability index (S_t), and category-specific transaction volumes ($V_{c,t}$).

The analysis leverages the merchant category classifications available in the harmonized dataset (primarily high-transacting categories), including examples such as:

- Groceries and Supermarkets (MCC ≈ 5411),
- Telecommunication Services (≈ 4814),
- Eating Places and Restaurants (≈ 5812),
- Miscellaneous Personal Services (≈ 7299),
- Digital Goods – Games (≈ 5816).

These categories display heterogeneous responses to approval adjustments due to differences in transaction frequency, average ticket size, P2M volume share, and historical fraud/decline rates ($BD_{i,t} + TD_{i,t}$).

7.7.1 Core Sensitivity Metrics

For a marginal perturbation δ in the approval rate associated with merchant category c (or entities predominantly serving that category), the first-order impacts are:

$$\frac{\partial V_{c,t}}{\partial \alpha_{c,t}} = E_c > 0 \qquad \text{(category-level volume elasticity)}, \tag{20}$$

$$\frac{\partial \Pi_t}{\partial \alpha_{c,t}} \approx V_{c,t} + \alpha_{c,t} \frac{\partial V_{c,t}}{\partial \alpha_{c,t}} \qquad \text{(net throughput gain)}, \tag{21}$$

$$\frac{\partial R_t}{\partial \alpha_{c,t}} = (BD_{c,t} + TD_{c,t}) \left(V_{c,t} + \alpha_{c,t} \frac{\partial V_{c,t}}{\partial \alpha_{c,t}} \right) \qquad \text{(risk amplification)}, \tag{22}$$

$$\frac{\partial S_t}{\partial \alpha_{c,t}} = -\frac{1}{\sum_i V_{i,t}} \frac{\partial R_t}{\partial \alpha_{c,t}} + \frac{R_t}{(\sum_i V_{i,t})^2} \frac{\partial (\sum_i V_{i,t})}{\partial \alpha_{c,t}} \qquad \text{(stability trade-off)}. \tag{23}$$

7.7.2 Numerical Stress-Testing Scenarios by Category

The following targeted perturbations extend the system-wide stress tests to category level:

1. **Approval rate increase** ($\alpha_{c,t} \to \alpha_{c,t} + 0.01$ or $+1\%$):

   - High-volume, low-fraud categories (e.g., Groceries/Supermarkets, Restaurants): strong positive volume elasticity $\to$ large $\Delta\Pi_t > 0$, modest $\Delta R_t \to$ net $\Delta S_t > 0$ (stability gain).
   - Digital Goods/Games: higher elasticity but elevated baseline fraud $\to$ substantial $\Delta V_{c,t}$ yet potentially larger $\Delta R_t \to$ possible $\Delta S_t < 0$.

2. **Approval rate decrease** ($\alpha_{c,t} \to \alpha_{c,t} - 0.01$ or -1%):

   - High-elasticity categories (e.g., Telecom, Restaurants): sharp volume contraction $\to$ significant $\Delta\Pi_t < 0$, but meaningful risk reduction may preserve or improve S_t.
   - Low-elasticity categories (e.g., Miscellaneous Services): muted volume loss $\to$ smaller throughput penalty with persistent risk exposure.

7.7.3 Marginal Revenue-to-Risk Prioritization

Elasticities E_c are estimated from the dynamic panel model:

$$V_{c,t} = \beta_0 + \beta_1 V_{c,t-1} + \beta_2 \alpha_{c,t} - \beta_3 F_{c,t} + \varepsilon_{c,t}, \tag{24}$$

where the short-run elasticity is captured by β_2. Categories are then ranked according to the marginal revenue-to-risk ratio:

$$\frac{\partial \Pi_t / \partial \alpha_{c,t}}{\partial R_t / \partial \alpha_{c,t}}. \tag{25}$$

High-ratio categories (typically essential retail such as groceries and restaurants) justify more permissive approval policies, while low-ratio or high-fraud categories (e.g., certain digital goods) warrant tighter controls.

7.7.4 Practical Implications for the UPI Ecosystem

- Categories with high P2M share and low historical failure rates exhibit favorable sensitivity profiles: modest approval increases deliver substantial volume gains with contained incremental risk.
- High-transacting digital categories require cautious policy adjustments, as fraud amplification can rapidly offset throughput benefits.
- The analysis supports differentiated, category-aware approval thresholds rather than uniform rules across banks and PSPs.

Computational complexity remains tractable at $\mathcal{O}(T \cdot C)$ for category-level perturbation sweeps, where C is the number of merchant categories, making the procedure scalable for monthly monitoring of the UPI dataset panels.

7.8 Summary of Numerical Findings

- The hybrid model yields 18–25% higher revenue.
- Convergence is achieved within 15–20 periods.
- Adaptive learning absorbs demand shocks efficiently.
- Variance in revenue decreases by nearly 50% relative to static pricing.

8 Discussion

The proposed framework demonstrates computational efficiency and revenue superiority over static methods.

Integration of forecasting and optimization enables adaptive responsiveness to market changes.

8.1 Limitations

- Linear demand assumption,
- Single-product focus,

- No competitive interaction model,
- ARIMA assumes stationary demand.

Future extensions may incorporate nonlinear demand, multi-product optimization, and competitive game-theoretic models.

9 Conclusion and Future Work

This study developed an integrated computational framework for dynamic pricing in e-commerce, combining demand forecasting, revenue optimization, and adaptive learning. The proposed model unifies elasticity-based demand estimation with constrained optimization and iterative price adjustment, enabling data-driven and scalable pricing decisions in uncertain and high-volume transactional environments.

The framework offers several theoretical and computational advantages. First, closed-form optimal solutions are derived under concavity assumptions, ensuring analytical tractability. Second, the adaptive learning mechanism provides convergence guarantees under appropriate step-size conditions. Third, the modular optimization structure supports computational scalability for large-scale transaction datasets. Finally, robustness analysis demonstrates stable performance under demand uncertainty and parameter perturbations.

Future research directions include extending the framework to multi-product and combinatorial pricing settings, incorporating stochastic and distributionally robust programming formulations, and integrating reinforcement learning for fully online decision-making. Empirical validation using large-scale real-world e-commerce and UPI transaction datasets will further assess practical effectiveness and operational impact.

Declarations

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The authors declare no competing interests.

Ethical Approval:

This article does not contain any studies involving human participants or animals performed by any of the authors.

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Data Availability

Dataset publicly available at GitHub: `https://github.com/vprema917/Indian-E-Commerce-Data`

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